Overreaction in House Price Expectations*

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Abstract

House prices play an important role in economic boom and bust cycles. However, little is known about the behavioral foundations of house price expectations. Using behavioral finance models, we investigate the cognitive factors behind the formation and revision process of house price expectations. We conduct a series of online studies with U.S. homeowners before and after the Fed's first meeting (Pre-study and Main Study, $N = 1,415$) and follow up with the same sample ($N = 1,024$) after the Fed's second meeting of the year. We explore the market uncertainty about the Fed's policy rate decision and design optimistic and pessimistic macroeconomic prediction treatments. In the Main Study, we elicit homeowners' short-term house price expectation priors, expose them to the treatments, and then measure house price posteriors. We find that homeowners *overreact* to information treatments relative to the Bayesian benchmark. Homeowners also exhibit asymmetric and optimistic belief revisions, suggesting that motivated reasoning can drive house price expectations. Property value and experienced house price growth history also influence the price expectation updating process. We observe significant price expectation shifts in the Follow-up study, indicating that homeowners actively monitor the macroeconomic outlook. We also detect an increase in reported exposure to news referencing Fed meetings. Our paper highlights the importance of mapping the micro-foundations of house price expectations on the verge of monetary policy changes.

Keywords: House prices, expectations, asymmetric reaction, Bayesian updating, experiment, belief entropy.

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I Introduction

The 2008 Great Recession, triggered by the burst of the housing bubble and subprime mortgages, highlighted the critical role of the housing market in the U.S. economy (Kuchler et al., 2023). Overly optimistic house price expectations were the primary cause of the pre-recession housing boom and subsequent bust (Shiller, 2007). In the wake of the financial crisis, there has been renewed research interest in understanding housing market price expectations.[1] Research findings reveal that homeowners tend to have more volatile and optimistic short-term house price expectations compared to their long-term views (Case et al., 2012). These expectations are influenced by recent price changes (Armona et al., 2019; Fuster et al., 2022), and optimistic price projections can causally affect house buying and selling decisions (Bottan and Perez-Truglia, 2020; Bailey et al., 2019). Housing market expectations also have substantial material consequences for households, as homes constitute a large portion of the asset wealth of U.S. homeowners (Bottan and Perez-Truglia, 2020; Eggleston et al., 2020). However, existing literature still lacks a comprehensive explanation of how house price expectations are formed and why they deviate from *rational* decision benchmarks. Leveraging online and field experiments can help identify the behavioral biases and cognitive mechanisms behind subjective economic expectations, which are not easily accessible through secondary data sources (Manski, 2004). Our paper addresses this gap using a series of incentivized and pre-registered survey experiments, studying how U.S. homeowners form and update their price expectations in response to economic information.

Using cognitive models from the behavioral finance literature, we investigate whether homeowners *overreact* or *underreact* to optimistic and pessimistic news relative to the Bayesian benchmark and, consequently, how they update their beliefs about short-term

[1]Pre-recession research on this topic specifically focused on market efficiency and primarily used time series modeling to identify the determinants of housing price dynamics (see Case and Shiller (1988, 1990); Engelhardt (1994)). For instance, Case and Shiller (1988) report a robust inertia effect in house price changes across major U.S. metros. However, they also note that inertia only explains a small variation in prices and emphasize the need to understand individual decision noise in price movements. There are also regular household surveys (e.g., University of Michigan Surveys of Consumers) investigating how economic expectations change. However, existing institutional surveys mainly elicit households' perceptions about past housing prices without employing an experimental framework (de Bruin et al., 2023).

house price changes in their zip codes.[2] We are interested in the extent to which homeowners react to macroeconomic developments, particularly to potential federal funds rate policy changes. This is especially important from a policy-making perspective, as monetary policy becomes more effective when homeowners show higher house price expectation revisions in the face of policy changes.[3] Moreover, our study design allows us to determine to what extent recently documented behavioral factors in the housing market, such as experienced house price change (Armona et al., 2019), market entry status (Kuchler et al., 2023), and asset value (Barberis, 2018) affect the expectation revision process.

Why study reaction to potential macroeconomic policy changes and associated house price belief updates with finance-based cognitive models? House price expectations are intertwined with key economic indicators. For instance, in conventional macroeconomic models, the user cost of housing capital is positively related to the real interest rate and negatively affected by expected short-term house price growth dynamics (Mishkin, 2007). Inflated house price growth expectations can drive down the user cost of capital and substantially increase housing demand. Moreover, the user cost of capital directly affects housing rent, which is part of the Consumer Price Index (CPI) (Leung, 2023). However, recent work shows that after the 2008 Great Recession, the correlation between house prices and macroeconomic fundamentals has decreased; instead, house price dynamics have begun to exhibit a higher correlation with financial market changes (Leung and Ng, 2019). This shift can be partly explained by increasingly available lending options for homeowners that enable borrowing against home equity; inflated house prices also inflate home equity values, granting access to more leveraged debt positions (Duca et al., 2019). For today's homeowners, a house is not only a dwelling unit but also an important investment tool. Therefore, house price beliefs exhibit similar patterns to stock market price expectations (Kuchler et al., 2023). Although the growing behavioral finance literature has documented different mental models explaining households' stock market price expectations and trading volume (Barberis, 2018), there is little evidence regarding the cognitive determinants of house price beliefs (Kuchler et al., 2023).

[2] We use price expectations and price beliefs interchangeably throughout the text.

[3] For instance, Lee and Ma (2023) show that in connected housing markets, the monetary policy transmission channels are more effective when house prices are mainly driven by macroeconomic factors.

We make several contributions to the existing literature. First, previous studies investigating house price expectations mostly used *backward-looking information* treatments. For instance, Armona et al. (2019) and Fuster et al. (2022) constructed their experimental treatments using past house price change information to analyze house price belief updates. While this approach has some advantages (e.g., observing belief updates when perceived price changes do not align with actual price movement history), it does not capture house price expectation revisions when homeowners are exposed to different market predictions. Moreover, in actual market situations, homeowners primarily pay attention to predictions about potential future market trends and then revise their house price expectations. Some follow-up studies address this gap by exposing households to information treatments with different housing market predictions (Bottan and Perez-Truglia, 2020; Chopra et al., 2023). However, these studies only use optimistic market predictions, forecasting either relatively higher or lower house price increases.[4] We design *forward-looking information* treatments with both optimistic and pessimistic housing market predictions. Having both directions in our study setup allows us to investigate how homeowners revise their house price beliefs when faced with favorable or unfavorable market forecasts.

Moreover, we do not include point estimates in our information treatments and only use predictions with upward or downward market trends. It is typical for financial market professionals to incorporate detailed forecasts with point estimates into their decisions.[5] However, households mostly rely on news media sources, where market forecasts typically appear as directional predictions of key market indicators. In fact, we use the market forecasts of two leading nationwide realtor services in designing our information treatments. Therefore, our study setup resembles households' typical economic news consumption environment, increasing the external validity of our findings.[6]

[4] It is worth noting that Fuster et al. (2022) also employed an information treatment where households could buy a market prediction about future house price changes. However, that treatment only contained optimistic information, predicting upward changes in house prices.

[5] For instance, see Bordalo et al. (2020) for the importance of detailed projections and expectation revisions in the Survey of Professional Forecasters (SPF) and the Blue Chip Survey. They also show that those revisions can explain the information rigidity in financial markets.

[6] Using point estimates in information treatments may have some benefits. For instance, a homeowner expecting a 4% price increase may find a 2% price increase prediction to be a pessimistic information shock (Bottan and Perez-Truglia, 2020). However, it is usually challenging to identify the "natural expectation baseline" of households.

Second, our data collection occurs on the verge of the Federal Reserve's (Fed) decision either to hold its policy rate at a historically high level to combat rising CPI rates or to reduce interest rates to avoid the likelihood of an economic recession.[7] This context yielded two almost equally likely macroeconomic outlooks for homeowners: i) a tight monetary policy potentially yielding a *seller's market* (optimistic forecast for future house price growth) or ii) a moderate interest rate regime potentially yielding a *buyer's market* (pessimistic scenario predicting downward trends in house prices) in the U.S. housing market. Hence, our study setup allows us to assess the micro-foundations of house price expectations when homeowners are exposed to one of the probable macroeconomic change forecasts. Recent macroeconomics research is increasingly adopting micro-foundations and heterogeneous agent modeling to better reflect housing market dynamics for improving policy suggestions (Kaplan and Violante, 2018). The closest to our study is Binder et al. (2023), who provide long-term federal funds rate projections to households to measure their house price expectations. We extend this research line by designing information treatments predicting either upward or downward changes in the federal funds rate.

Third, the behavioral finance literature documents three predictable stock market patterns: i) stock returns are *excessively volatile*, ii) a stock's return over the past three to five years is negatively correlated with its expected short-term returns, exhibiting *mean reversion*, and iii) a stock's past six to twelve-month return predicts its short-term returns with a positive sign, showing *momentum* (Barberis, 2018). Indeed, excess variance, mean reversion, and short-term momentum in prices are also well-documented stylized facts in the housing market (Case and Shiller, 1988; Cutler et al., 1991; Glaeser et al., 2014; Glaeser and Nathanson, 2017). Recent studies explain these stock market patterns with (over-)extrapolative beliefs (i.e., over-relying on the predictive power of past returns) (Barberis et al., 1998; Greenwood and Shleifer, 2014; Barberis et al., 2018; Barberis, 2018).[8] Glaeser and Nathanson (2017) show that extrapolative beliefs can also explain excess volatility, mean reversion, and momentum in house price dynamics. The emerging consensus in the literature is that extrapolative

[7]See Blinder (2023) for a discussion about the "hard landing" outcome of a high-interest rate regime.

[8]Barberis (2018) discusses that the mean reversion pattern can be explained by over-extrapolative beliefs. In general, mean reversion or long-term reversal in asset prices can be the artifact of negative investor sentiment after holding inaccurate extrapolative beliefs.

beliefs are related to *reaction* to news, which subsequently affects how investors update their beliefs about the asset's future price potential (Barberis, 2018). Hence, we offer key insights into primary house price dynamics in the housing market by investigating homeowners' reactions to macroeconomic changes and identifying their behavioral foundations.

We proceed in three stages. In the Pre-study, we survey homeowners to document their primary dwelling property's key features (market value, size, zip code, etc). Then we conduct Main ($N = 1,415$) and Follow-up ($N = 1,024$) studies one day after the Fed's first and second meeting in the year, respectively.

In the Main Study, we elicited homeowners' probabilistic 6-month-ahead house price change expectation *priors* (August 2024 year-over-year change) for their residential zip codes. Specifically, study participants were given 100 tokens representing percentage points and instructed to allocate them among 11 potential house price change intervals (ranging from "at least 4% decrease" to "at least 4% increase") based on their expectations. We incentivized these expectations using the Binarized Quadratic Scoring Rule (BQSR) method. Participants were informed that their incentive bonuses would be determined based on Zillow's market report after August 2024.

We randomly assigned the Main Study participants to either the *Seller's Market Signal* or *Buyer's Market Signal* experimental information treatments using a between-subject study design. We compiled the information treatments from Zillow's and Redfin's—two leading nationwide realtor services—housing market predictions for 2024.[9] According to an independent third-party assessor, the average market forecast accuracy of these two realtor services was around 71%. This 71% accuracy served as a *signal-to-noise* ratio in our study design, allowing us to investigate how homeowners update their housing market price beliefs relative to the Bayesian benchmark. We informed homeowners about this accuracy score before they were exposed to the information treatments.

The Seller's Market Signal information piece highlighted that an unfavorable macroeconomic outlook might cause higher policy rates to be maintained by the Fed throughout 2024, leading to limited housing inventory in the market. Under this scenario, the 2024 housing

[9] We did not disclose the information sources to homeowners.

market was predicted to be a *seller's market*. On the other hand, the Buyer's Market Signal forecasted tamed inflation levels, lower Fed policy rates, and increased housing inventory in the market, predicting more favorable conditions for homebuyers.[10] It is worth reiterating that both scenarios had almost the same chance of being realized at the time of our information treatments. Therefore, our study exposed participants to one of the almost equally likely market predictions to study homeowners' reactions to optimistic (Seller's Market Signal) and pessimistic (Buyer's Market Signal) economic forecasts. After providing the Main Study participants with information pieces, we elicited their incentivized *posterior* beliefs about 6-month-ahead year-over-year house price changes for their zip codes.

Our primary results are based on Bayesian belief updating analyses, investigating the cumulative probability assigned by homeowners for a 6-month ahead year-over-year price increase in their residential zip codes. Specifically, we focus on identifying whether homeowners underreact or overreact to a potential Fed policy change and how they consequently update their house price expectations. We find that homeowners significantly overreact to both optimistic (Seller's Market Signal) and pessimistic (Buyer's Market Signal) information pieces compared to the Bayesian decision benchmark. Overreaction to information has also been documented among professional forecasters of macroeconomic indicators (Bordalo et al., 2020) and has been associated with excess volatility in markets (Augenblick et al., 2023). Hence, our finding explains observed fluctuations in house prices, especially in the short-term (Glaeser and Nathanson, 2017).

The literature offers different explanations about the causes of overreaction. Ba et al. (2022) find that overreaction is likely generated by the complexity of the decision problem. Another factor triggering overreaction to our experimental information pieces might be cognitive noise. Laboratory studies show that cognitive noise and imprecision can mediate belief revision (Ba et al., 2022; Augenblick et al., 2023). Therefore, homeowners' overreaction to

[10] Almost-zero policy rates during the COVID-19 pandemic allowed homebuyers to finance their purchases with lower mortgage rates. Additionally, many existing homeowners refinanced their mortgages to secure more favorable rates. After COVID-19, the Fed's very steep and rapid policy rate hike may have prevented a potential supply of existing homes. This is mainly because homeowners might prefer to retain their relatively lower mortgage rates when considering moving to a different location or upgrading their homes. At the time of our study, the general perception among homeowners was that obtaining pandemic-era low mortgage rates would be impossible in the foreseeable future in the then-existing policy environment.

information might stem from the complexity of the housing market and their cognitive noise.

Our study design allows us to shed light on the role of cognitive noise in housing market expectations. Having individual probabilistic prior and posterior belief distributions enables us to measure the entropy (i.e., belief uncertainty) in price expectations and link it to belief updating. Our investigations reveal that homeowners with relatively higher uncertainty (i.e., higher entropy) in their prior house price expectations exhibit greater belief changes than those with relatively lower uncertainty in their prior beliefs. This finding suggests that homeowners with a higher noise level in their price expectations might be prone to a greater degree of house price expectation changes when exposed to economic information.

Our full and sub-sample analyses consistently show that homeowners are prone to *base-rate neglect* when updating their house price beliefs. A Bayesian thinker's belief updating is not a function of priors, but the base-rate neglect bias leads to discounting the information value of priors and reduces belief confidence (Möbius et al., 2022). Laboratory studies have shown that individuals with the base-rate neglect bias mostly rely on recent information, underweight the history of market signals, and exhibit extrapolative beliefs; extrapolative beliefs cause a stochastic belief formation process and consistent fluctuation of market prices around the asset's true value (Benjamin, 2019; Barberis, 2018).

Overall, we detect asymmetric belief updating in response to optimistic and pessimistic information. Homeowners revise their price expectations more significantly when presented with the optimistic Seller's Market Signal than with the pessimistic Buyer's Market Signal. Asymmetric belief updating and overreaction to positive information have been associated with high confidence in expectations; this belief revision pattern might also be explained by discounting the information value of "bad" signals (Möbius et al., 2022).

Based on Pre-study responses, we classify homeowners as "On-Market" if they indicate that they are considering selling their home in 2024 and as "Off-Market" if they do not have any market entry intentions. Emerging literature shows that asset ownership status can affect expectations. For instance, renters are more informed about recent market trends compared to homeowners (Kuchler et al., 2023). However, it is not clear if the intention of selling one's home affects market expectations. We find that both On- and Off-Market homeowners overreact to optimistic and pessimistic housing market predictions to the same extent. However, On-Market homeowners exhibit symmetric belief updating, whereas Off-Market homeowners overreact more to the Seller's Market Signal information treatment compared to the Buyer's Market Signal. Apart from this difference in symmetry, the belief updating behaviors of the On- and Off-Market homeowner sub-samples are statistically indistinguishable. Our findings suggest that homeowners' housing market price expectation updates are mostly unaffected by their intention to enter the market. Since homes constitute a significant share of household wealth and are increasingly becoming an investment tool, it is not surprising that homeowners' processing of market information is not affected by their current market entry intentions.

We also observe statistically different belief updating differences across reported property values. Homeowners with relatively lower-valued homes overreact more to the optimistic economic forecasts. On the contrary, homeowners with relatively higher-valued homes overreact to optimistic and pessimistic economic outlook forecasts with the same belief updating magnitude. This finding aligns with the evidence that expectations are closely related to an asset's current value and future price potential (Adam and Nagel, 2023; Barberis et al., 2018).

We estimate each zip code's past 12-month price growth slope based on Zillow's monthly zip-code-level typical home value data for 2023. Using the median value of these estimated slope distributions, we classify homeowners into relatively lower and higher experienced 12-month price growth sub-samples. Similarly, we conduct the same exercise with the past 36-month price growth data.

Homeowners exhibit statistically different belief-updating patterns based on the price growth they experienced in their zip codes. All homeowners show asymmetric belief updating and overreact more to the optimistic price prediction. However, this effect is larger for homeowners with a relatively lower experienced 12-month price growth. In other words, experiencing a relatively lower 12-month price growth leads to a greater overreaction level to the optimistic macroeconomic outlook prediction. We find the same effect when comparing lower and higher experienced 36-month price growth sub-samples. These results cannot be reconciled with *diagnostic* expectations, which explains a wide range of expectation revisions about leading macroeconomic indicators (Bordalo et al., 2020). Diagnostic expectations would predict overreaction to the optimistic (pessimistic) economic forecast after homeowners experience a relatively higher (lower) price growth trend. The motivated belief formation framework better explains our findings. Under this framework, economic agents prefer holding favorable views and gain additional utility from holding optimistic expectations (Möbius et al., 2022; Bénabou and Tirole, 2002). This optimism bias can increase in a "bad" state to make it more tolerable (Bénabou and Tirole, 2016).

We develop a model explaining our study findings. In the model, an economic agent first distorts the Bayesian belief updating process by *overreacting* to the information signal and exhibiting the base-rate neglect bias. The first stage yields a set of potential *biased posterior* beliefs. However, our agent still aspires to be *rational* to some extent. In the second stage of the decision-making process, the agent picks the optimal biased posterior that maximizes their utility function. Consistent with the motivated belief updating framework, the utility function includes *instrumental utility* (conventional utility of holding unbiased beliefs), *belief utility* (optimism bias), and *cognitive noise* of holding biased beliefs (Möbius et al., 2022; Engelmann et al., 2024; Drobner and Goerg, 2024). We simulate our model predictions and show that it predicts a higher level of belief updating asymmetry when the agent assigns a higher weight to belief utility (i.e., optimism bias). We also show that this bias can be exacerbated when cognitive noise is higher. Homeowners might be prone to a higher degree of optimism bias when recent price changes have been relatively lower. Higher entropy in prior beliefs can also reduce cognitive cost. Our model also predicts symmetric belief updating in the absence of optimism bias, coupled with a lower level of cognitive noise Hence, we offer a new two-stage belief determination framework that can explain the complex expectation formation process of homeowners.[11]

In the Follow-up study, we re-elicit probabilistic house price expectations for the same target month used in the Main Study. We find that homeowners significantly elevated their probabilistic beliefs about observing a year-over-year house price increase in their zip codes in

[11] We reserve "updating" for the first stage of the Bayesian belief revision. In the second stage, the agent determines the optimal biased posterior by finding the biased posterior that maximizes their utility function.

August 2024. Interestingly, our Main Study treatments remained effective in the Follow-up study decisions. In the entire Follow-up study sample, the average homeowner revised their probabilistic beliefs upwards regarding a house price increase. However, homeowners who received the Buyer's Market Signal in the Main Study exhibited a higher magnitude belief revision than those from the Seller's Market Signal treatment. This result indicates that homeowners actively follow dynamic market changes and update their beliefs, as the Follow-up study did not contain any new information treatment or reference to the macroeconomic outlook. This finding overlaps with the reported results of Binder et al. (2023), as they also show the persistence of treatment effects in the short term.

Do documented belief updates have any effect on market entry intentions? We elicit homeowners' willingness to sell their homes in the Follow-up study using the same survey instrument utilized in the Pre-study. Using the same measure allows us to track down On- and Off-Market homeowners' market exit and entry intentions in the Follow-up study, respectively. We find that, in the Follow-up study, 21% of Off-Market homeowners are willing to enter the market and consider selling their homes, while 23% of On-Market homeowners indicate that they don't have any intention to sell their properties during 2024. The proportion of market exit intentions in the On-market subgroup is not statistically different than the proportion of market entry intentions among Off-Market homeowners. This finding suggests that, under a worsening macroeconomic outlook and uncertain Fed policy rate conditions, the housing inventory, at least, does not increase.

In the Follow-up study, we also analyze the market exit intentions of our On-Market subsample. We find that homeowners who increase their probabilistic beliefs about observing a year-over-year house price increase in their zip codes are more likely to exit the market. Interestingly, this effect is entirely driven by the homeowners who were in the Seller's Market Signal experimental treatment in the Main Study. More specifically, a 10 percentage points (p.p.) increase in the house-price-increase probability leads to a 3 p.p. increase in the market exit intention among homeowners who were exposed to the optimistic economic forecast in the Main Study. Bottan and Perez-Truglia (2020) also report that increasing house price expectations reduces the probability of selling one's property.

Finally, we investigate to what extent homeowners follow Fed meetings or become cognizant of news mentioning Fed meetings. In both the Main and Follow-up studies, we ask subjects to indicate what recently caught their attention in economic or finance-related news. We list "Fed's meeting" along with other options such as "Stock Market Surge," "Treasury Auctions," etc. We create an indicator variable for cases when homeowners select the "Fed's meeting" option in their responses. In the Main Study, around 28% of homeowners indicated hearing about a Fed meeting in the news. We do not observe differences across study treatments, as our survey instrument was designed to measure retrospective news exposure. We also do not detect any information treatment effects on the reported expected mortgage rates. However, in the Follow-up study, the proportion of homeowners who report being exposed to news mentioning "Fed's meeting" increased to 34%. Interestingly, we find that this increase is driven by homeowners who report being Republicans and had been in the Seller's Market Signal treatment in the Main Study. Republican homeowners expect a mortgage rate of around 5.68% by the end of 2024, compared to 5.44% expected by non-Republican homeowners.

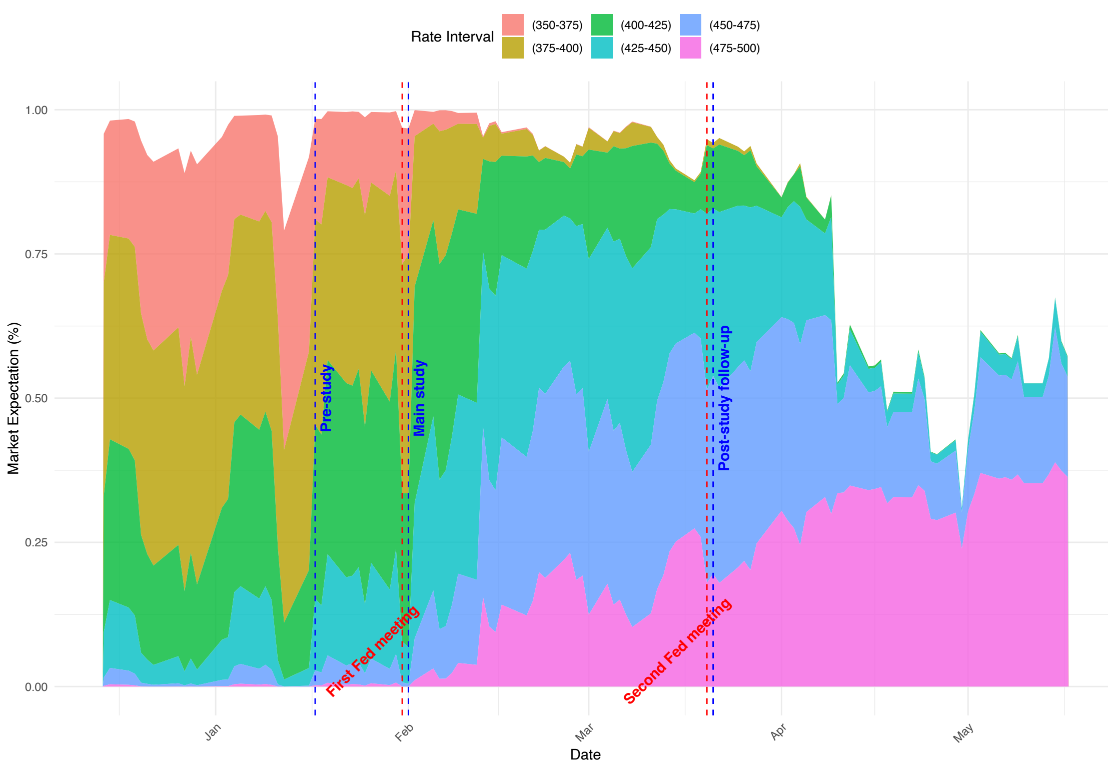
The rest of the article is structured as follows. We discuss the macroeconomic policy environment in Section II. We present experimental design details and other study methodologies in Section III. We outline our modeling approach and derived predictions in Section IV. Section V presents our findings. The final section positions our study within the relevant literature and concludes.

II Macroeconomic Policy Context

We conduct our studies under unique economic conditions where the unfolding macroeconomic outlook could lead to two different interest rate policies. The Federal Reserve (Fed) increased the Federal Funds Effective Rate (FFER) from 0.08% in February 2022 to around 5.33% in August 2023 due to exponentially rising inflation rates.[12] This policy rate hike created the tightest monetary policy environment since 2007, pushing the average 30-year

[12]See https://fred.stlouisfed.org/series/FEDFUNDS

fixed mortgage rate to approximately 7.8% by the end of 2023.[13] The rising borrowing costs led to a decrease in the Case-Shiller U.S. National Home Price Index in the last quarter of 2023 and also triggered downward trends in CPI inflation rates (FRED, 2024). At the time of our study, the decreasing inflation rate sparked cautious optimism in the market that the Fed might significantly lower the FFER to the 3.75%-4.25% range by the end of 2024. Under this optimistic scenario, the market anticipated the first Federal Funds Rate cut at the second Fed meeting in March 2024. However, another countervailing view in the market was that the inflation rate might spiral out of control again, forcing the Fed to maintain higher rates for a longer period.



Note: This figure displays the market expectation probabilities (y-axis) for selected Federal Funds Effective Rate (FFER) intervals (colored) and the study timings. The market expectations were retrieved from the CME FedWatch Tool (between mid-December 2023 and mid-May 2024) and reflect probabilities for potential FFER intervals after the Fed's December 2024 meeting. The dashed blue lines indicate our study dates, while the dashed red lines indicate the Fed meeting dates. Main and follow-up studies were conducted one day after the corresponding Fed meetings.

Figure 1: Market Expectations of Selected Fed Rate Intervals with Study Timings

[13]See https://fred.stlouisfed.org/series/MORTGAGE30US

Figure 1 displays the timings of our studies and the market's beliefs about future FFER intervals by the end of 2024. Our Pre-study was conducted in mid-January 2024 with U.S. resident homeowners, approximately two weeks before the Fed's first meeting of the year. In the Pre-study, we collected data about the features of their primary residences (home value, number of bedrooms, etc.) and location zip codes. We also elicited their probabilistic intentions regarding the possibility of listing their homes for sale in 2024.

The Main Study took place a day after the Fed's January 31 meeting in 2024. As Figure 1 shows, the market's expectations between our Pre and Main Studies about future FFER policies remained almost stable and cautiously optimistic.[14] It is worth noting that the Main Study was conducted before the first CPI print of the year; therefore, the market was still maintaining favorable views about the monetary policy conditions for 2024.

We conducted the Follow-up study one day after the Fed's March meeting and re-elicited posterior beliefs. As Figure 1 shows, the macroeconomic outlook has significantly changed between the Main and Follow-up studies. During the first quarter of 2024, the CPI inflation rate exhibited upward trends, leading to an unfavorable macroeconomic outlook for Fed policy rate cuts. The market has revised its optimistic Fed policy rate projection down to the 4.24%-4.75% range with around 60% probability by the end of 2024. At the time of our Follow-up study, the predictions of the Seller's Market Signal treatment started manifesting in the U.S. economy. Therefore, the Follow-up study allowed us to measure house price belief updates caused by macroeconomic changes.

III Experimental Design

We conducted a brief pre-study survey to identify United States resident homeowners and elicit primary characteristics of their households and dwelling properties.[15] We used prolific.co—an online crowdsourcing platform—to recruit households who own the property they live in. The platform regularly updates its members' basic demographic information and allows re-

[14] Although we observe probability changes on our Main Study day, it must be noted that there is usually some lag for rate policy expectations to be reflected in the data. Therefore, it is plausible to assume that at the time of our Main Study, the aggregate market expectations were very close to the Pre-study context.

[15] Screenshots of key experimental procedures are provided in the Appendix

searchers to apply appropriate screenings for studies. We used the "I own the property I live in" screening, so our survey request was only published to homeowner households.[16]

Around 92% of households owned houses, with 73% living in urban areas. The majority of households reported having properties valued between \$150,000 and \$750,000 (79%), with 2-4 bedrooms (89%) and sized between 1,000 and 3,000 square feet (82%). Close to 52% of homeowners had mortgage rates between 2.50% and 5.50%, while around 33% reported not having any mortgage financing for their properties. Moreover, 71% of homeowners reported an annual household income between \$50,000 and \$175,000.[17]

We also elicited homeowners' Willingness to Sell (WTS) their homes during the year. The elicitation question included answers ranging from "Not at all (0% probability)" to "I will definitely consider selling." We classified homeowners as "Off-Market" if they selected the "Not at all (0% probability)" option in the question; otherwise, we labeled them as "On-Market." Table S1 shows that around 40% of homeowners had an intention of selling their homes during 2024.

Main Study: We conducted the Main Study a day after the Fed's first meeting of the year and only invited homeowners from the Pre-study.[18] Figure 2 shows the residential zip codes of our Main Study homeowners. As Figure 2 illustrates, our participants are predominantly from major U.S. metros.

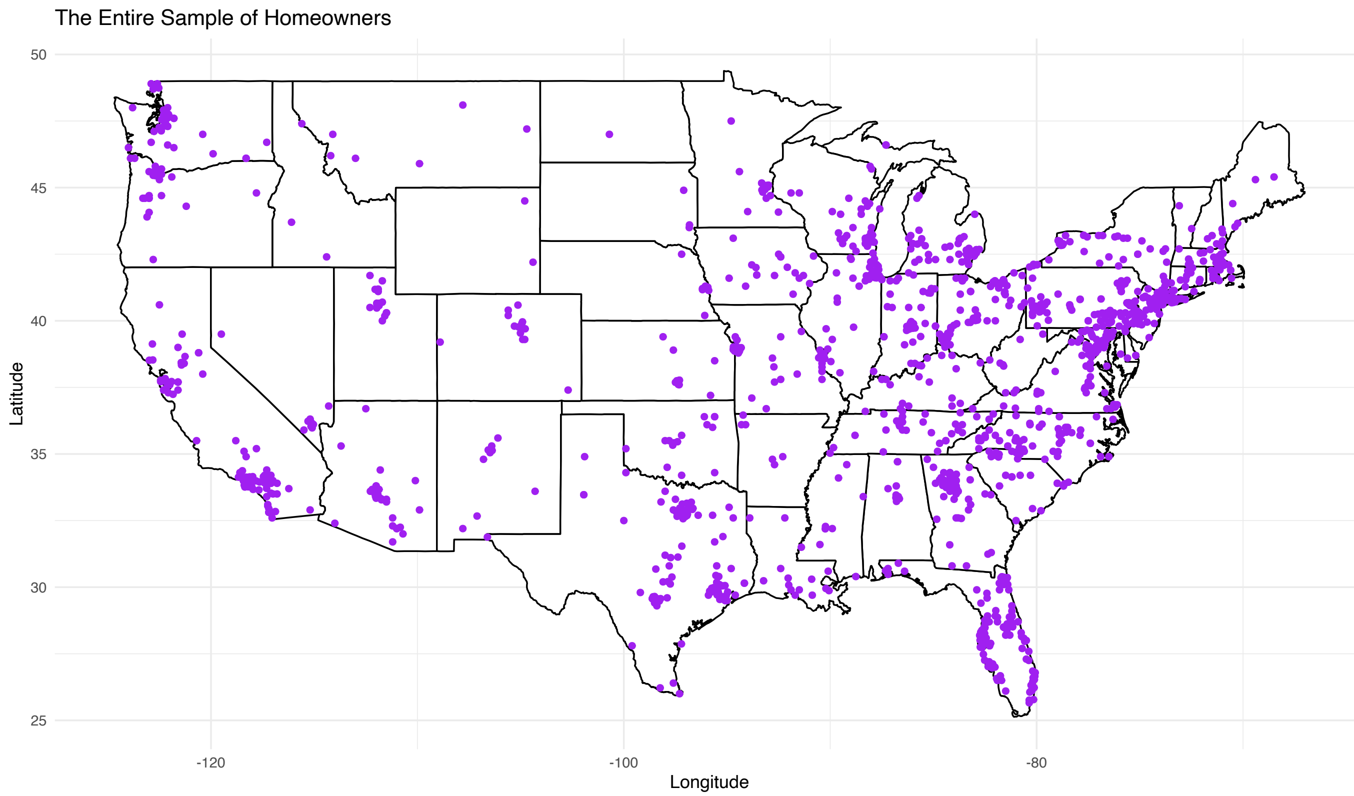
Participants were introduced to general study rules and procedures and informed that they would make a 6-month-ahead house price year-over-year change prediction for their residential zip codes. In other words, they had to predict the average house price change

[16] This screening question is part of a demographic questionnaire that users complete before joining the platform. The platform also regularly repeats the questionnaire. Therefore, we exclude the possibility that participants could misreport their homeownership status to be eligible for the study. Moreover, recent studies also report the high reliability of Prolific's screening filters (Exley and Nielsen, 2024).

We also restricted eligibility to homeowners with 90% or above approval rate. The approval rate reflects the extent to which other researchers deemed the participants' previous study participation to be of high quality. The participants were compensated with a \$11.15/hour rate, and the median completion time was around 2 minutes.

[17] We recruited United States resident homeowners for our Pre-study survey. Our final Pre-study sample size was 2,489 after excluding 25 participants for providing invalid zip codes per USPS's zip code master list. We invited $1,415$ homeowners for the Main Study. Table S1 compares Pre-study homeowners included in our Main Study to those excluded. We find almost no difference between these subgroups across a wide range of characteristics.

[18] Participants were compensated at an approximate rate of \$17.00/hour, and the median completion time was approximately 9 minutes.



Note: This figure displays the location of the Main Study participants (N=1410) based on the constructed geolocation points using zip codes. We excluded five subjects residing in Hawaii and Alaska for presentation purposes.

Figure 2: Location of Homeowners across the United States

in August 2024 with respect to August 2023. We presented 11 potential house price change intervals: {At least−4.00%}, {−3.99% to−3.00%}, {−2.99 to%−2.00%}, {−1.99% to−1%}, {−0.99% to−0.01%}, {0.00%}, {0.01% to 0.99%}, {1.00% to %1.99%}, {2.00% to 2.99%}, {3.00% to 3.99%}, and {At least 4.00%}. Each homeowner had 100 tokens representing 100 percentage points and allocated tokens among the intervals reflecting their probabilistic beliefs about house price changes.

We incentivized beliefs with the Binarized Quadratic Scoring Rule (BQSR) using this formula: $\pi_{lottery} = 1 - (\mathrm{I}_{Event\ dummy} - \pi_{belief})^2$. Based on this method, after August 2024, the experimenter randomly selects one interval and checks whether the actual house price change of each homeowner's zip code falls into the selected interval. The $\mathrm{I}_{Event\ dummy}$ term is 1 if the selected interval includes the actual house price change; otherwise, it is 0. Accordingly, $\pi_{belief} = \frac{\text{Number of Tokens in the Selected Interval}}{100}$. Then, we calculate $\pi_{lottery}$ for each homeowner. In the last stage, each homeowner plays a lottery, which has a $\pi^i_{lottery}$ chance of earning \$2.00. Participants were informed that the bonus rewards would be realized after August 2024 using Zillow's market report for each zip code.

It is always challenging to explain incentive methods, especially when they include formulas and multiple steps (Stantcheva, 2023). To address this issue, we designed an online calculator to facilitate the learning process. Participants could allocate 100 tokens to the intervals and select their expected true house price change in August. Then, the calculator showed the final $\pi^i_{lottery}$ for each interval based on the token allocation. Moreover, at the final stage of the instructions, we included a quiz question about the BQSR method, and participants could only proceed to the next stage after providing an accurate answer.

Priors, Information Treatments, and Posteriors: We elicited house price change priors and then randomly assigned homeowners to either the Seller's Market Signal or the Buyer's Market Signal condition.[19] We compiled the market predictions for both information treatment pieces from Redfin and Zillow's 2024 market expectation reports. We informed study participants that the information pieces were compiled using market predictions provided by realtor services, but we did not disclose our sources. We also mentioned that, according to an independent third-party assessor, the average price prediction accuracy of our sources is 71%.[20] We required homeowners to spend at least 20 seconds reading the information pieces. The average time spent reading the treatment pieces was close to 40 seconds.

The Seller's Market Signal experimental condition predicted that a high-interest rate regime would continue throughout the year, leading to a limited housing inventory supply and, consequently, high house prices:

> *We predict higher for longer is the key regarding mortgage rates looking ahead. Recent inflation news gives the impression that mortgage rates are likely to hold fairly steady and inventory will remain much lower than pre-pandemic norms. The lack of housing inventory is keeping prices elevated for all homes. Buy-*

[19] Table S2 shows that there is no statistical difference between treatment groups across primary demographic and property characteristics.

[20] According to the third party, Zillow and Redfin had 67% and 74% accuracy in price predictions with a 5% confidence interval, respectively (https://tinyurl.com/5n8u5txw).

ers have few options and may still have to compete for the few homes that are available, which can lead to higher sale prices.

In turn, the Buyer's Market Signal condition provided a different prediction, highlighting an improving macroeconomic outlook, lower interest rates, and an increase in housing supply:

> *We predict mortgage rates will decline throughout the year. We're starting to see signs of a shift toward a buyer's market as pandemic-driven inflation takes its last gasps and mortgage rates come down. More sellers are expected to list their homes for sale. We expect these trends to continue, leading to home listings to rise and prices to fall. So, home prices will fall because supply will rise more than demand. That's a favorable shift for home buyers.*

Both predictions were primary market expectations reported by the sources at the time of our study. After the information treatments, homeowners were asked to provide their probabilistic house price change beliefs one more time. We also informed study participants that both their prior and posterior beliefs had the same chance of being used to realize bonus rewards.

The Main Study concluded with a set of manipulation check questions. We also asked participants to indicate what caught their attention in recent economic news. One of the options was "Fed's meeting." This measure allowed us to track whether our information treatments increased attention to monetary policy.

Design Choices: We did not include a control condition with no information treatment. Armona et al. (2019) show that belief updating can also happen when subjects are not provided with information treatments. Agranov and Ortoleva (2017) show that repetitive measures in an experimental setting are prone to stochastic variations. Experimental subjects update their decisions even when the information set is fixed. Haaland et al. (2023) question using a control group (with no information provision) in studies where the primary dependent variable of interest is belief updating. They stress that provided information can trigger different mental mechanisms for posterior beliefs, making it hard to interpret the comparison of treatment results to no-information-control outcomes.

Assume that three primary variations can potentially drive posterior beliefs: stochastic behavior (Agranov and Ortoleva, 2017), economic thinking, and confusion inspired by information pieces (Haaland et al., 2023). We can assume that information confusion will be equally distributed in treatment posteriors. Moreover, information should also reduce the magnitude of stochastic behavior in posteriors. Therefore, comparing treatments will inform the differential effects of optimistic and pessimistic economic information on belief updating. However, in the control group, the only variation will be stochastic behavior, oscillating in posteriors compared to priors. Thus, comparing treatment posteriors to the control posterior won't cleanly identify the effect of economic thinking on belief revisions. Additionally, during our study period, there were two primary market predictions, and we were interested in measuring the difference between their effects on expectation revisions. Our Follow-up Study shows that homeowners actively consume economic news and update their beliefs, suggesting that a no-information-control design might not be a realistic decision baseline.

Follow-up Study: We conducted the Follow-up Study a day after the Fed's second meeting of the year. The second Fed meeting was particularly important for the pessimistic Buyer's Market Signal information condition. Based on market sentiment at the beginning of the year, the Fed would start cutting policy rates in the second meeting, provided that the macroeconomic outlook was favorable.

We only invited homeowners from the Main Study to participate in the Follow-up Study. The response rate was 72% (N=1,024), which is comparable to other online studies (Binder et al., 2023).[21]

In the Follow-up Study, we reminded homeowners about the BQSR method and then asked them to provide their August 2024 year-over-year house price change expectations for their zip codes. We used the Main Study's belief elicitation instruments. Consenting homeowners replaced their new house price prediction posteriors with the ones they provided in the Main Study. Thus, it was in the best interest of Follow-up Study participants to provide their thoughtful predictions to refine their chances of earning the $2.00 bonus reward. We concluded the Follow-up Study with manipulation questions and the economic news consumption measure that we used in the Main Study.

[21] Participants were compensated at a $12.00/hour rate, and the median completion time was 4 minutes.

Data Quality Evidence: Roth and Wohlfart (2020) propose using the number of non-zero intervals in probabilistic belief elicitation methods as a data quality measure. The intuition is that study participants not engaging in economic deliberation might prefer providing corner beliefs (allocating all tokens to one interval). It is possible that this approach discounts belief certainty and assumes that corner beliefs are less likely to be truthful. However, considering the complexity of predicting short-term house price changes, it is plausible that corner beliefs, at least, are not bonus-reward-maximizing strategies.

For each homeowner, we calculate the average number of intervals with at least two intervals having non-zero tokens. We find that around 97% of Main Study participants allocated non-zero tokens to at least two intervals. Moreover, the average non-zero interval length for priors and posteriors is 6.11 and 5.95, respectively. Our data quality level is comparable to other online studies and panel surveys conducted by the New York Fed (Armantier et al., 2013; Roth and Wohlfart, 2020).[22]

IV Motivating Model

We develop a modeling approach that integrates the Bayesian belief updating process and its biases into the motivated beliefs framework. Specifically, we focus on *overreaction* to signals relative to the Bayesian benchmark and the base-rate neglect bias that leads to re-scaling prior beliefs (Benjamin, 2019). We then introduce a motivated belief utility framework (Möbius et al., 2022; Engelmann et al., 2024; Drobner and Goerg, 2024).

We follow a two-stage approach. First, an agent i updates their beliefs when facing new evidence. This updating process is prone to biases, which we assume are triggered by characteristics of the decision environment that are not captured in the model. The distorted Bayesian belief updating process yields a set of biased posteriors. In the second stage, agent i employs an additional utility maximization approach to determine their optimal biased posterior.[23]

[22]For instance, Roth and Wohlfart (2020) report that the average length of intervals with at least two intervals having non-zero tokens is 4.24 in their data.

[23]In this regard, our modeling approach is closer to other theoretical frameworks, where agents still strive to be rational while failing to follow some decision theoretic axiomatic rules (Maćkowiak et al., 2023).

Model Setup: There are two potential states s in the future, where $s \in \{G, B\}$. Agent i has the prior belief that the probability of $s = G$ is $\pi^i_{G,prior}$, such that $\pi^i_{G,prior} + \pi^i_{B,prior} = 1$.

In the first stage, agent i receives either an optimistic (g) or pessimistic (b) signal z ($z \in \{g, b\}$), where $p(g|G) = p(b|B) = q$. Then, based on the Bayesian framework, agent i should determine $\pi_{G,posterior}$ after receiving the z signal and before the realization of the true state as follows:

$$\pi_{G,posterior} = \frac{\pi_{G,prior} \cdot p(z|G)}{\pi_{G,prior} \cdot p(z|G) + \pi_{B,prior} \cdot p(z|B)} \tag{1}$$

where $p(z|G)$ and $p(z|B)$ are the likelihoods of receiving signal z given that the states G and B will be realized, respectively. However, agent i has biases and updates their beliefs following this specification (Grether, 1980; Benjamin, 2019):

$$\pi_{G,posterior} = \frac{\pi^{\delta}_{G,prior} \cdot p(z|G)^{\beta}}{\pi^{\delta}_{G,prior} \cdot p(z|G)^{\beta} + \pi^{\delta}_{B,prior} \cdot p(z|B)^{\beta}} \tag{2}$$

where $\delta, \beta \geq 0$ represent the reaction level to the signal and base-rate neglect (re-scaling of priors), respectively. The strict Bayesian framework requires $\delta = \beta = 1$. Equation 2 can be expanded to a reduced form as follows (Möbius et al., 2022):

$$\begin{aligned} \text{logit}\left(\frac{\pi^i_{G,posterior}}{1 - \pi^i_{G,posterior}}\right) &= \delta \cdot \text{logit}\left(\frac{\pi^i_{G,prior}}{1 - \pi^i_{G,prior}}\right) + \\ \beta_G \cdot \log\left(\frac{q}{1-q}\right) \cdot I(z^i = g) &+ \beta_B \cdot \log\left(\frac{1-q}{q}\right) \cdot I(z^i = b) + \rho^i \end{aligned} \tag{3}$$

where I is a binary variable indicating the received signal type. Notice that equation 3 can be estimated using an OLS estimation without a regression constant.

The estimated parameters of equation 3 can identify Bayesian belief updating biases as follows:

– If estimated $\hat{\delta} = 1$, $\hat{\beta}_G = 1$, and $\hat{\beta}_B = 1$, then agent i strictly follows Bayesian belief updating.

– Agent i exhibits conservative (i.e., underreaction) belief updating if $\hat{\beta}_G < 1$ or $\hat{\beta}_B < 1$.

– However, agent i overreacts to the signal if $\hat{\beta}_G > 1$ or $\hat{\beta}_B > 1$.

– Agent i shows the base-rate neglect bias if $\hat{\delta} < 1$. This bias leads to the discounting of prior beliefs. The reverse of the base-rate neglect bias is the confirmation bias ($\hat{\delta} > 1$), where agent i only updates their belief if the signal aligns with their prior.

– Agent i is prone to asymmetric and optimistic belief updating if $\hat{\beta}_G > \hat{\beta}_B$.

– Conversely, agent i exhibits asymmetric and pessimistic updating if $\hat{\beta}_G < \hat{\beta}_B$.

We assume that when agent i distorts the Bayesian belief updating process, they end up with a set of potential biased posteriors. For instance, agent i can overreact to the signal with different magnitudes. Our second stage determines the optimal level of overreaction.

In the second stage, agent i determines the optimal biased posterior that maximizes their utility, which is specified as follows (Drobner and Goerg, 2024):

$$\begin{aligned} U(\pi_{G,posterior}) = \phi \cdot \underbrace{\pi_{G,posterior}}_{\text{Belief Utility}} + M \cdot \underbrace{(1 - \pi_G + 2 \cdot \pi_G \cdot \pi_{G,posterior} - \pi^2_{G,posterior})}_{\text{Instrumental Utility}} - \\ - \psi \cdot \underbrace{(\pi_G - \pi_{G,posterior})^2}_{\text{Cognitive Cost}} \end{aligned} \tag{4}$$

where π_G is the true probability of state G. In line with Drobner and Goerg (2024), we assume linearity for Belief and Instrumental Utilities, as we only need monotonicity to derive model predictions.

The Belief Utility term captures the notion that holding optimistic beliefs instantaneously grants positive utility. However, holding posterior beliefs closer to the true probability maximizes the chance of receiving the M reward.[24] If the M reward is small, agent i can maximize their utility by holding the most biased posterior belief. The final Cognitive Cost term balances Belief Utility. Agent i incurs a cognitive cost if they deviate from the true

[24] In our study, we incentivize beliefs. Hence, the functional form of the Instrumental Utility term comes from the BQSR setting.

probability.[25]

The parameters ϕ and ψ reflect the weight of Belief Utility (i.e., the degree of optimism bias) and Cognitive Cost in the utility function, respectively. We assume that the magnitude of ϕ is determined by individual characteristics; we spell out some of them below. We approximate ψ with the inverse of entropy in prior beliefs. The intuition is that when agent i has a higher level of prior belief uncertainty, they also underweight the cognitive cost.[26]

We calculate the entropy measure as follows:

$$Entropy^i = -\Sigma_k \pi^i_{Interval_k} log(\pi^i_{Interval_k}) \tag{5}$$

where k represents house price intervals (i.e., $k \in \{1, 2, 3, ..., 11\}$), and $\pi_{Interval_{i,k}}$ is agent i's number of percentage point allocations for the interval k. Our entropy measure is 0 when agent i allocates all tokens to one house price interval.

Figure 3 presents model-simulated biased posteriors to both positive (optimistic) and negative (pessimistic) signals when agent i has a high level of entropy ($\psi = 0.1$) in their priors. We observe that the optimal biased posteriors move further away from the Bayesian benchmark as agent i exhibits a higher degree of optimism bias (ϕ). Hence, agent i overreacts more to the optimistic information.

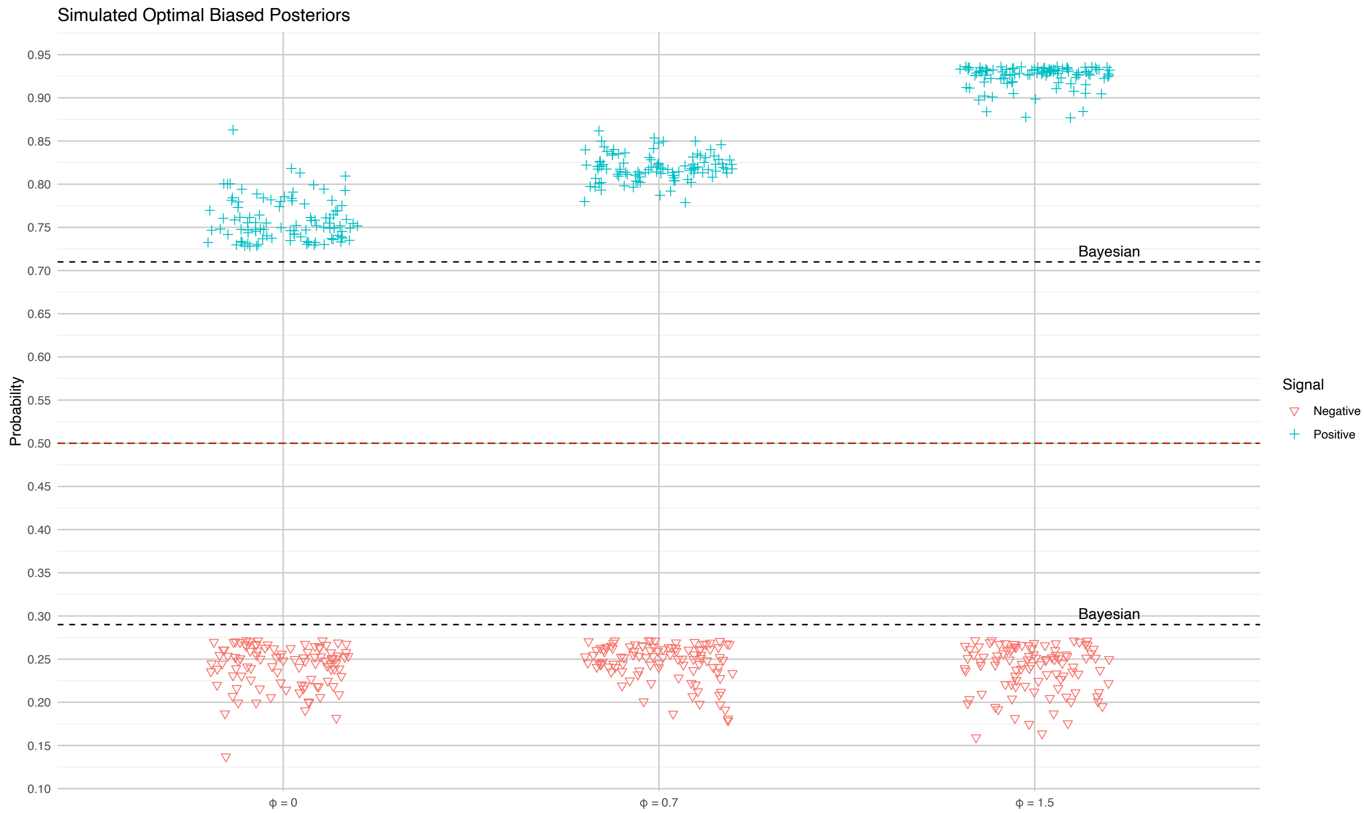
Figure S1 in the Appendix shows that when $\psi = 0.5$ (i.e., a relatively lower entropy level in priors), asymmetric overreaction to the optimistic signal only occurs when the optimism bias is very severe ($\phi = 1.5$). Hence, our model predicts that agent i becomes less vulnerable to optimism bias if they have a high level of certainty in their prior beliefs.

Predictions: Based on equation 4, the optimal biased posterior has this functional form:

$$\pi_{G,posterior} = \pi_G + \frac{\phi}{2 \cdot (M + \psi)} \tag{6}$$

[25] The intuition is that even if the future state is uncertain, agent i might have some *sense* about it. One can also think about this term as the cost of expected regret. We do not bring expectation into the utility framework, as we employ a static decision environment in our studies.

[26] If an agent is extremely uncertain about the future, their expected ex-post regret will be closer to zero. In other words, having maximum entropy in priors means that the agent assigned almost equal probabilities to potential future states. Hence, they cannot have a "near-miss" and will always feel minimal ex-post regret.



Note: We compare simulated biased posteriors across positive and negative signals. We set $\psi = 0.1$ (i.e., a higher prior belief entropy level). Each cluster holds 100 biased posteriors. We set the true and prior probabilities to 0.5 to reflect the macroeconomic environment in our Main study. M is normalized to 1 in simulations.

Figure 3: Simulated Biased Posteriors and Optimism Bias.

which is positively related to optimism bias (ϕ) and negatively affected by the weight of cognitive cost ($\psi = \frac{1}{Entropy}$).

Prediction 1: Behavioral finance suggests that optimism bias is directly related to the asset's value. It has been shown that financial analysts usually exhibit a higher level of optimism for growth stocks (which are relatively less valuable than value stocks) and small firms (Skinner and Sloan, 2002; Qian, 2009). Optimism is especially prevalent when owners of equity consider selling their assets, as it can help them cope with the negative effects of bad news (Bénabou and Tirole, 2016). Therefore, our first model prediction is that homeowners will be more prone to optimism if their home values are relatively lower than the market average. In model terms, we expect $\phi_{\text{low-value}} > \phi_{\text{high-value}}$, and consequently, $\pi_{G,posterior,\text{low-value}} > \phi_{G,posterior,\text{high-value}}$.

Prediction 2: Similarly, homeowners experiencing a relatively lower price growth trend in their zip code might self-select to be more optimistic to cope with their unfavorable market situation (Bénabou and Tirole, 2016). Hence, $\phi_{\text{low-price-trend}} > \phi_{\text{high-price-trend}}$, and consequently, $\pi_{G,posterior,\text{low-price-trend}} > \phi_{G,posterior,\text{high-price-trend}}$.

Prediction 3: Finally, as we show in Figure S1, a reduction in entropy increases the weight of cognitive cost. This leads to a lower level of optimism. Specifically, having $\frac{1}{\text{high-entropy}} < \frac{1}{\text{low-entropy}}$ leads to $\psi_{\text{high-entropy}} < \psi_{\text{low-entropy}}$. In turn, a lower weight of cognitive cost triggers a higher level of optimism, such that $\pi_{G,posterior,\text{high-entropy}} > \pi_{G,posterior,\text{low-entropy}}$.

V Results

We begin our discussion with manipulation check measures for our information treatment conditions in the Main Study. Table 1 presents the impact of our study treatments on seven different manipulation check measures. Homeowners responded to the manipulation check questions after being exposed to our Seller's or Buyer's Market Signal treatments, which can exhibit to what extent our experimental conditions induced different economic perspectives among study participants.

Table 1 column 1 shows that homeowners in the Seller's Market Signal experimental condition were 13 percentage points (p.p.) more likely to report that "it is a better time to sell a house" compared to buying one. In other words, our Seller's Market Signal treatment increased the perception that the housing market was more likely to be a seller's market. This result indicates that our treatments successfully triggered economic thinking aligned with the provided information pieces.

Can homeowners extrapolate future changes in other key macroeconomic indicators using our information pieces? Information treatments only provided directional predictions about the Fed's potential policy rate changes and mentioned trends in the CPI inflation rate. It is important to understand to what extent homeowners can establish a connection between the Fed's policy rate changes, CPI rate, and the overall macroeconomic outlook.

The Seller's Market Signal treatment predicted high interest and inflation rates. Table

Table 1: Manipulation Checks for Experimental Treatment Conditions (Main Study)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Seller's Market Signal	0.13***	−0.03	−0.05*	−0.03	−0.05**	−0.04	−0.03
	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
Constant	0.56***	0.25***	0.47***	0.31***	0.64***	0.56***	0.46***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	1415	1415	1415	1415	1415	1415	1415
Rsq	0.02	0.00	0.00	0.00	0.00	0.00	0.00

Note: This table presents manipulation checks for the Seller's Market Signal and Buyer's Market Signal experimental conditions. OLS regression coefficients and robust HC1 standard errors are reported. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$
Primary Measure: In column (1), the dependent variable was constructed using two survey questions that independently elicited respondents' opinions about general market conditions for selling and buying a house. A 5-point Likert scale was used, ranging from "A very bad time" to "A very good time," with a midpoint of "Neither a good time nor bad time." The dependent variable was coded as 1 if the respondent indicated a relatively better time to sell a house than to buy one. The "Unsure/No opinion" option was also provided.
Other potential channels: Columns (2)-(4) display the influence of the treatment conditions on six-month-ahead expectations regarding employment, economic growth, and household finances, respectively. A 5-point Likert scale was used, ranging from "Will significantly decrease" to "Will significantly increase," with a midpoint of "Will remain about the same." The "Unsure/No opinion" option was also provided. The dependent variable was coded as 1 if the respondent indicated either "Will significantly increase" or "Will somewhat increase."
Columns (5)-(7) show the relationship between the treatments and six-month-ahead optimism about personal finance, the financial prospects of people living in the same zip code, and the United States, respectively. A 5-point Likert scale was used, ranging from "Very pessimistic" to "Very optimistic," with a midpoint of "Neutral." The "Not sure/No opinion" option was also provided. The dependent variable was coded as 1 if the respondent indicated either "Somewhat optimistic" or "Very optimistic."

1 columns 3 and 5 exhibit that homeowners in this experimental condition expected worsening economic growth and deteriorating conditions for their personal finances. However, we do not detect any effect of our treatments on the expected national unemployment level and general national household financial conditions. Homeowners' expectations about the financial prospects of other households living in their zip code or in other parts of the United States are also not affected by the information treatments. We conclude that homeowners establish an association between high interest rates and worsening economic growth and personal finance conditions.

Table S3 presents the effect of our Main Study treatments on the economic perspective measures in the Follow-up Study. The Follow-up Study did not provide any economic information; however, it was conducted a day after the Fed's second meeting of the year and under very different macroeconomic conditions. Moreover, our measures in Table S3 also show to what degree our Main Study's experimental information treatments were persistent.

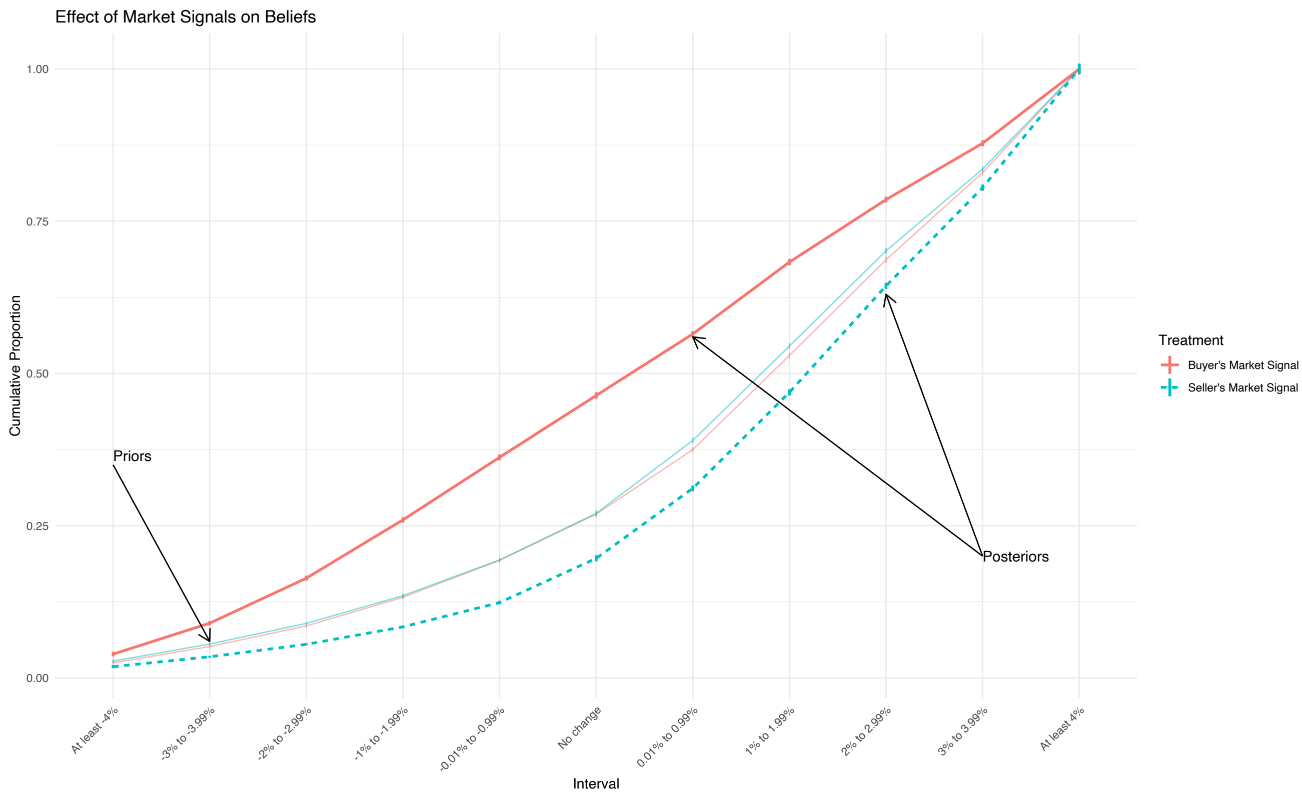
Table S3 shows that our treatment conditions still have some effect in the Follow-up Study. Homeowners in the Seller's Market Signal condition are eight percentage points (p.p.) more likely to think that the housing market is more suitable for selling houses compared to those in the Buyer's Market Signal condition. We also find that homeowners in the Seller's Market Signal condition exhibit a more pessimistic view of the financial conditions of other households living in their zip codes and in other parts of the United States.

V.A Determinants of House Price Priors

Figure 4 displays the CDFs of house price change priors and posteriors in the Main Study.[27] Since we measured house price expectation priors before our experimental information treatments, we should not observe any statistical difference between the Seller's and Buyer's Market Signal conditions. Indeed, Figure 4 shows that our randomization of the treatment assignments among study participants was successful, and there is no difference between house price priors across study conditions. Moreover, Table S2 provides multiple hypothesis testing results comparing key demographic and property characteristics of information treatments. Table S2 shows that our treatment groups are balanced across all measures.

Table S4 provides analyses investigating the determinants of house price priors for the entire sample. In other words, we analyze the key determinants of house price change priors. We focus on the cumulative percentage points allocated to five house price intervals reflecting a 6-month-ahead year-over-year house price increase (ranging from 0.01% to 0.99% to At least 4.00%) in homeowners' zip codes: $\Pi^i_{>0\%} = \sum_{k=1}^{5} \pi^i_{prior,\text{Interval}_k}$. We estimate OLS regressions as follows:

[27] Figure S2 provides density distributions of allocated prior and posterior tokens to all house price change intervals.



Note: This figure shows the Cumulative Distribution Functions for housing price growth expectation priors and posteriors.

Figure 4: CDFs of Priors and Posteriors

$$\Pi^i_{>0\%} = \beta_0 + \beta_1 Control^i + \rho^i \tag{7}$$

where, ρ^i represents errors.

Results of regressions using equation 7 are provided in Table S4. Table S4 column 1 reiterates that our treatment conditions did not affect prior beliefs, confirming our previous discussions. We also find that being Republican and considering selling property does not affect priors. Thus, partisanship and being On- or Off-Market do not influence measured house price increase priors.

Table S4 shows that homeowners with a high-value property are more likely to assign a higher cumulative prior probability for a 6-month-ahead year-over-year house price increase. Moreover, homeowners with a higher annual household income are also more likely to allocate more tokens, predicting a positive change in short-term house prices. Thus, we conclude that property value and household income affect house price priors and, consequently, can mediate the effect of our information treatments on posteriors.

We also investigate whether experienced house price changes in homeowners' zip codes affect their prior beliefs. We use Zillow's Home Value Indices for the previous 12 and 36 months to estimate zip-code-specific house price change trends.[28] We estimate a basic linear trend regression for each zip code as follows:[29]

$$HVI_t^z = \beta_0^z + \beta_1^z t + \rho^z \tag{8}$$

where, t is a time trend $(1, 2, ...)$, HVI_t^z is Zillow's Home Value Index for each zip code z, and ρ^z is the zip-code-specific error.

Using equation 8, we estimate β_1^z for the 12- and 36-month periods for each zip code. Then we split our data based on the median value of β_1^z for 12- and 36-month periods. We create a dummy variable if a zip code's estimated β_1^z for the 12-month period is lower than the median value. This binary variable represents zip codes that have a relatively lower previous 12-month price growth trend in our sample. We conduct the same exercise for the 36-month period and create a binary variable representing zip codes that have a relatively lower previous 36-month price growth trend in our sample.

Table S4 shows that homeowners living in zip codes with relatively lower 12-month price growth trends are more likely to assign a lower probability for a 6-month-ahead year-over-year price increase for their zip codes. This can be evidence of short-term momentum beliefs. However, we don't find any influence of the 36-month price growth trend on house price increase priors.

[28]We conducted our Main Study in February 2024. At the time of our study, housing market statistics for January 2024 were not available. Therefore, we assume that the homeowner's "previous month" was December 2023, when we conducted the Main Study. Thus, the previous 12 and 36 months coincide with 2023 and 2021-2023, respectively. We omit the COVID-19 year as it saw unusual housing market trends and can be regarded as a "structural shock year." Hence, we also do not consider price change history before 2020.

[29]We use the linear trend assumption in prices (Greene, 2003, page 21). We do not consider potential non-stationary and other time-series properties in our data. We elect to estimate a basic linear trend in home values of each zip code as a proxy for the experienced price change trend.

V.B Bayesian Analyses of Belief Updates and Posteriors

We estimate equation 3, where $\pi^i = \sum_{k=1}^{5} \pi^i_{\text{Interval}_k}$, i.e., all allocated tokens to house price increase intervals by homeowner i.[30] Table 2 column 1 shows the results of the Bayesian analysis for the pooled sample. The estimated $\hat{\delta}$ is 0.72, and it is statistically smaller than 1. This finding indicates that homeowners' house price increase posteriors do not satisfy the invariance property (Möbius et al., 2022). Put differently, homeowners' priors affect their belief updating, and since $\hat{\delta} < 1$, they exhibit the base-rate neglect bias. The base-rate neglect bias leads to the re-scaling of prior beliefs, and in the equilibrium (after a series of belief updates), all homeowners will converge to 0.5 probability (Benjamin, 2019). The base rate neglect bias will also cause fluctuations in short-term price expectations.

Table 2, column 1 also provides estimated $\hat{\beta}_{\text{Seller's Market Signal}}$ and $\hat{\beta}_{\text{Buyer's Market Signal}}$ parameters, reflecting the reaction to our information pieces or the magnitude of the belief revision. We find that both parameters are greater than 1, indicating overreaction to information pieces. However, the magnitude of overreaction to the Seller's Market Signal is statistically greater than the overreaction to the Buyer's Market Signal ($3.76 > 2.76$). Thus, we detect a higher magnitude of belief updating to the optimistic prediction than the reaction to the pessimistic information piece; this finding also shows asymmetric and optimistic belief updating among homeowners.

Table 2, columns 2 and 3 provide sub-sample analyses comparing On- and Off-Market homeowners' belief updating. The conducted Chow-test ($F\text{–}stat = 0.17$) cannot reject the null hypothesis of no difference between sub-samples. The only difference is that, in the On-Market sub-sample, we do not detect asymmetric belief updating. Overall, On- and Off-Market sub-samples exhibit similar belief revision patterns as the pooled sample. We conclude that the market entry status of homeowners mostly does not affect how they revise their house price expectations.

Table 2, columns 4 and 5 present sub-sample analyses for low- and high-valued prop-

[30] We restrict our data to *correct* belief revisions (Möbius et al., 2022). The belief revision is *correct* if $\pi^i_{posterior} \geq \pi^i_{prior}$ when homeowners are in the Seller's Market Signal condition; otherwise, $\pi^i_{posterior} \leq \pi^i_{prior}$ when in the Buyer's Market Signal. We also convert boundary beliefs 1 and 0 to 0.99999 and 0.00001, respectively.

Table 2: Bayesian Updating Analyses
(Main Study)

		Belief updating about House Price Increase			
		On vs Off Market Property		*Low vs High Valued Property*	
	Pooled	On-Market	Off-Market	Low-Valued	High-Valued
	(1)	(2)	(3)	(4)	(5)
δ	0.72***	0.73***	0.71***	0.62***	0.82***
	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)
$\beta_{\text{Seller's Market Signal}}$	3.76***	3.58***	3.90***	4.60***	2.75***
	(0.22)	(0.35)	(0.29)	(0.31)	(0.29)
$\beta_{\text{Buyer's Market Signal}}$	2.76***	2.85***	2.68***	3.40***	2.09***
	(0.21)	(0.33)	(0.27)	(0.30)	(0.27)
N	1269	523	746	685	584
Rsq	0.64	0.64	0.64	0.57	0.74
$\mathbb{P}$ ($\beta_{\text{Seller's Market Signal}} = \beta_{\text{Seller's Market Signal}}$)		*0.25*		*<0.01*	
$\mathbb{P}$ ($\beta_{\text{Buyer's Market Signal}} = \beta_{\text{Buyer's Market Signal}}$)		*0.36*		*<0.01*	
Chow Test for sub-sample models:		$F-stat = 0.17$		$F-stat = 20.19$	
		p-value= 0.91		*p-value*< 0.01	
$\mathbb{P}$ ($\delta = 1$)	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
$\mathbb{P}$ ($\beta_{\text{Seller's Market Signal}}$=1)	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
$\mathbb{P}$ ($\beta_{\text{Buyer's Market Signal}}$=1)	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
$\mathbb{P}$ ($\beta_{\text{Seller's Market Signal}}=\beta_{\text{Buyer's Market Signal}}$)	< 0.01	0.15	< 0.01	< 0.01	0.12

Note: This table presents structural Bayesian analyses for the entire sample of homeowners and sub-samples. The dependent variable is the posterior odd ratio for logit beliefs. The variable δ shows the prior odd ratio for logit beliefs. Robust HC1 standard errors and OLS estimates are reported. *p<0.1; **p<0.05; ***p<0.01

erties.[31] We find that these two sub-samples exhibit statistically different belief-updating behaviors (Chow-test ($F\text{–}stat = 20.19$)). In the low-valued sub-sample, homeowners show an optimistic overreaction to the Seller's Market Signal information. However, in the high-valued sub-sample, belief revisions are symmetric to optimistic and pessimistic information pieces and are smaller in magnitude than in the low-valued sub-sample. We conclude that homeowners with relatively lower-valued properties tend to overreact more to information and exhibit an optimistic belief revision bias.

Table 3 provides Bayesian analysis results for experienced house price growth trends in the last 12- and 36-month periods. Table 3, columns 1-3 show findings for the pooled data and for low and high experienced 12-month house price growth trend sub-samples, respectively. We

[31] We used the median-split to create low- and high-valued property sub-samples.

Table 3: Bayesian Updating Analyses for Experienced Price Growth (Main Study)

		Belief updating about House Price Increase			
		Experienced 12-month Price Growth		*Experienced 36-month Price Growth*	
	Pooled	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)
$\boldsymbol{\delta}$	0.72***	0.65***	0.78***	0.63***	0.80***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
$\boldsymbol{\beta}_{\text{Seller's Market Signal}}$	3.76***	4.29***	3.32***	4.58***	2.98***
	(0.22)	(0.33)	(0.29)	(0.33)	(0.29)
$\boldsymbol{\beta}_{\text{Buyer's Market Signal}}$	2.76***	3.06***	2.50***	3.11***	2.49***
	(0.21)	(0.30)	(0.29)	(0.31)	(0.28)
N	1269	620	628	627	621
Rsq	0.64	0.60	0.69	0.58	0.71
$\mathbb{P}$ ($\beta_{\text{Seller's Market Signal}} = \beta_{\text{Seller's Market Signal}}$)		*0.02*		*<0.01*	
$\mathbb{P}$ ($\beta_{\text{Buyer's Market Signal}} = \beta_{\text{Buyer's Market Signal}}$)		*0.11*		*0.09*	
Chow Test for sub-sample models:		$F - stat = 12.25$ *p-value*< 0.01		$F - stat = 17.39$ *p-value*< 0.01	
$\mathbb{P}$ ($\delta = 1$)	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
$\mathbb{P}$ ($\beta_{\text{Seller's Market Signal}}$=1)	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
$\mathbb{P}$ ($\beta_{\text{Buyer's Market Signal}}$=1)	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
$\mathbb{P}$ ($\beta_{\text{Seller's Market Signal}}$=$\boldsymbol{\beta}_{\text{Buyer's Market Signal}}$)	< 0.01	< 0.01	0.06	< 0.01	0.25

Note: This table presents structural Bayesian analyses for the entire sample of homeowners and sub-samples. The dependent variable is the posterior odd ratio for logit beliefs. The variable δ shows the prior odd ratio for logit beliefs. Robust HC1 standard errors and OLS estimates are reported. *p<0.1; **p<0.05; ***p<0.01

find that low and high-experienced price growth sub-samples are structurally different (Chow-test (F–$stat = 12.25$)). Homeowners experiencing relatively lower price growth overreact to the information pieces; however, the magnitude of the overreaction to the Seller's Market Signal treatment is greater than the belief revision magnitude in the Buyer's Market Signal. We see similar optimistic and asymmetric belief revision patterns in the high-experienced 12-month price growth sub-sample, albeit with lower magnitudes. We conclude that all homeowners exhibit optimistic overreaction, but the magnitude of the overreaction is larger when experienced 12-month price growth is relatively lower.

Table 3, columns 4 and 5 conduct the same analyses for experienced 36-month house price growth trends. Our findings mostly overlap with belief revision patterns for experienced last

12-month house price growth trends. Homeowners living in zip codes that saw relatively lower price growth trends over the last 36 months tend to optimistically overreact. However, homeowners who experienced relatively higher price growth trends in the last 36-month period overreact with lower magnitudes and symmetrically.

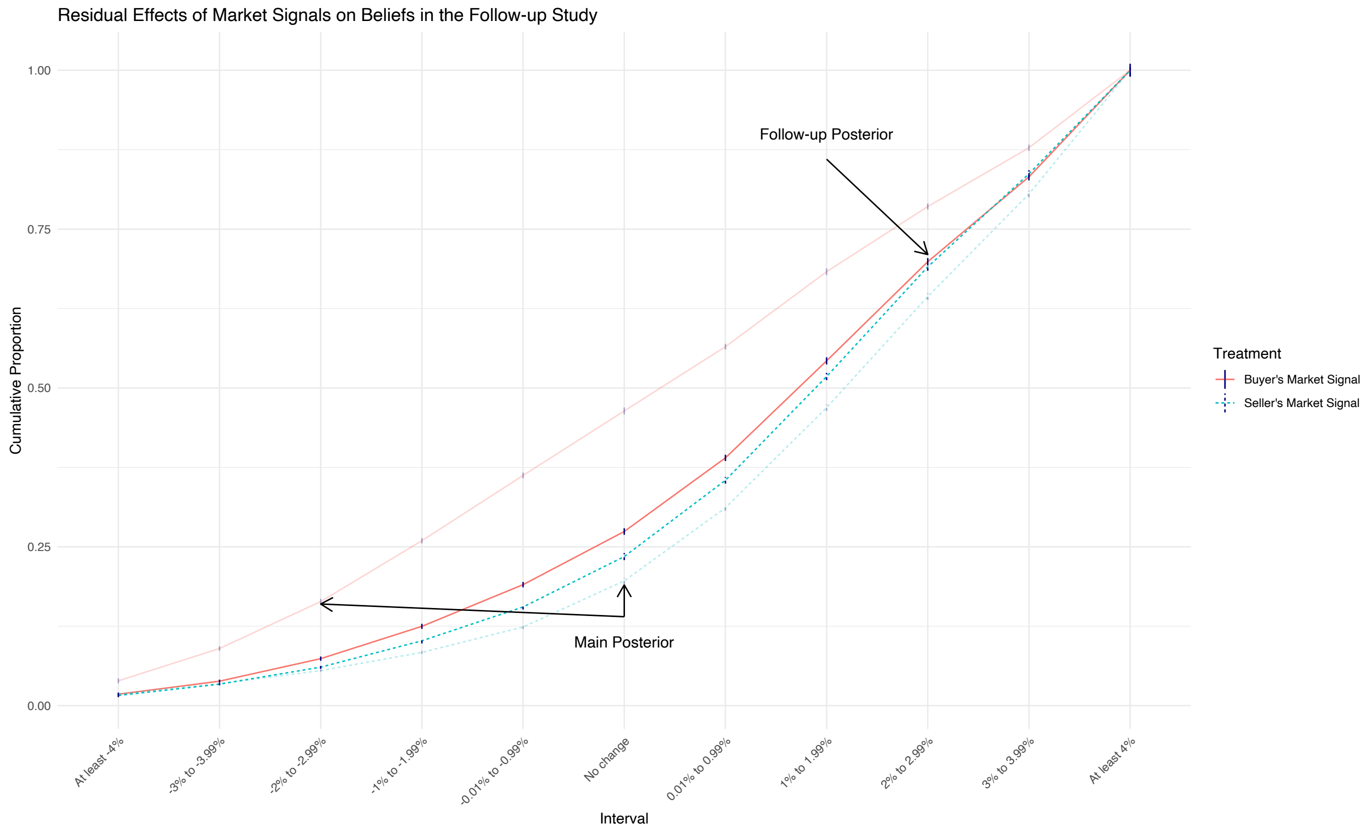
Overall, Table 3 shows that experienced recent price changes affect house price beliefs. We detect structurally different behaviors between low and high-experienced price growth trend sub-samples. Homeowners who saw relatively lower price growth trends in their zip codes are more likely to exhibit asymmetric and optimistic overreaction to the Seller's Market Signal condition. We also find that the magnitudes of overreaction are lower for homeowners experiencing relatively higher house price growth trends; moreover, for this subgroup, the overreaction is symmetric.

We do not detect the effect of partisanship on house price belief updates. Table S5 shows that there is no structural difference between Republican and non-Republican homeowners in terms of expectation revisions. However, below, we show that partisanship has some effect on belief updates in our Follow-up Study.

V.C Follow-Up Study Belief Updates and Posteriors

Figure 5 shows house price posterior beliefs for the Main and Follow-up Studies. We did not provide any information in the Follow-up Study. However, as Figure 1 shows, the macroeconomic outlook significantly changed between the Main and Follow-up Studies. Upward trends in CPI rates created uncertainty about the future path of the economy, precluding the Fed from cutting its policy rate at the second meeting of the year. When we conducted our Follow-up Study, the accuracy of the Seller's Market Signal started manifesting in the macroeconomic outlook. Therefore, our follow-up measures allow us to capture to what extent actual market and policy changes affect homeowners' house price expectations.

In Figure 5, we observe that homeowners in both the Seller's and Buyer's Market Signal treatments significantly shift their follow-up posteriors. However, we also observe that homeowners in the Buyer's Market Signal information condition exhibit a higher magnitude of belief revision. Nevertheless, after the Follow-up Study expectation revisions, homeown-



Note: We compare posteriors in Main and Follow-up Studies across information treatments.

Figure 5: Posteriors Main and Follow-up Studies.

ers who were exposed to the Seller's Market Signal information piece appeared to be more optimistic than participants in the Buyer's Market Signal treatment. This suggests that our information treatments persisted even after almost two months since our Main Study.

We modify equation 3 to estimate belief revisions in the Follow-up Study with respect to Main Study posteriors as follows:

$$\text{logit}\left(\frac{\pi^i_{G,posterior,Main}}{1-\pi^i_{G,posterior,Main}}\right) = \delta \cdot \text{logit}\left(\frac{\pi^i_{G,posterior,Follow-up}}{1-\pi^i_{G,posterior,Follow-up}}\right) + \beta_G \cdot I(z^i = g) + \beta_B \cdot I(z^i = b) + \wedge^i + \rho^i \tag{9}$$

where posteriors represent cumulative percentage points for all house price increase intervals and $\wedge^i$ includes individual controls.

Table 4 presents OLS regression results using the specification in equation 9. As observed in Figure 5, Table 4 confirms that homeowners increased their Follow-up posteriors about

Table 4: Bayesian Updating Analyses
(Follow-Up Study)

		Belief updating about House Price Increase			
	(1)	(2)	(3)	(4)	(5)
$\boldsymbol{\delta}$	0.27***	0.27***	0.27***	0.27***	0.27***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$\boldsymbol{\beta}_{\text{Seller's Market Signal}}$	2.81***	2.69***	2.50***	3.05***	2.98***
	(0.31)	(0.32)	(0.34)	(0.43)	(0.44)
$\boldsymbol{\beta}_{\text{Buyer's Market Signal}}$	3.81***	3.68***	3.88***	4.18***	4.37***
	(0.26)	(0.29)	(0.31)	(0.41)	(0.41)
Republican		0.41	−0.22	−0.24	−0.29
		(0.39)	(0.54)	(0.54)	(0.54)
$\boldsymbol{\beta}_{\text{Seller's Market Signal}}$*Republican			1.32*	1.28	1.41*
			(0.78)	(0.79)	(0.79)
Experienced 12-month Price growth (Low)				−0.40	
				(0.51)	
$\boldsymbol{\beta}_{\text{Seller's Market Signal}}$*Experienced 12-month Price growth (Low)				−0.64	
				(0.72)	
Experienced 36-month Price growth (Low)					−0.78
					(0.52)
$\boldsymbol{\beta}_{\text{Seller's Market Signal}}$*Experienced 36-month Price growth (Low)					−0.11
					(0.73)
N	1024	1024	1024	1007	1007
Rsq	0.39	0.39	0.39	0.40	0.40
$\mathbb{P}$ ($\beta_{\text{Seller's Market Signal}}$=$\boldsymbol{\beta}_{\text{Buyer's Market Signal}}$)	0.01	0.01	< 0.01	0.05	0.02

Note: This table presents Bayesian analyses for the Follow-up study. The variable δ shows the Main Study posterior beliefs about house price increase. Robust HC1 standard errors and OLS estimates are reported. *p<0.1; **p<0.05; ***p<0.01

experiencing a year-over-year house price increase in their zip codes in August 2024. However, the magnitude of belief revision is larger for homeowners who were in the Buyer's Market Signal condition in the Main Study.

Table 4 also shows that Republican homeowners who were exposed to the Seller's Market Signal treatment in the Main Study were more likely to revise their Follow-up posteriors upward with a higher magnitude than non-Republican homeowners. Interestingly, we do not detect any effect of experienced price growth trends on belief revisions in the Follow-up

Study; this finding suggests that our information treatments might nudge homeowners to pay more attention to the economic fundamentals of the housing market. Below, we provide some evidence that our information treatments at least induced greater attention to Fed meetings in our sample.

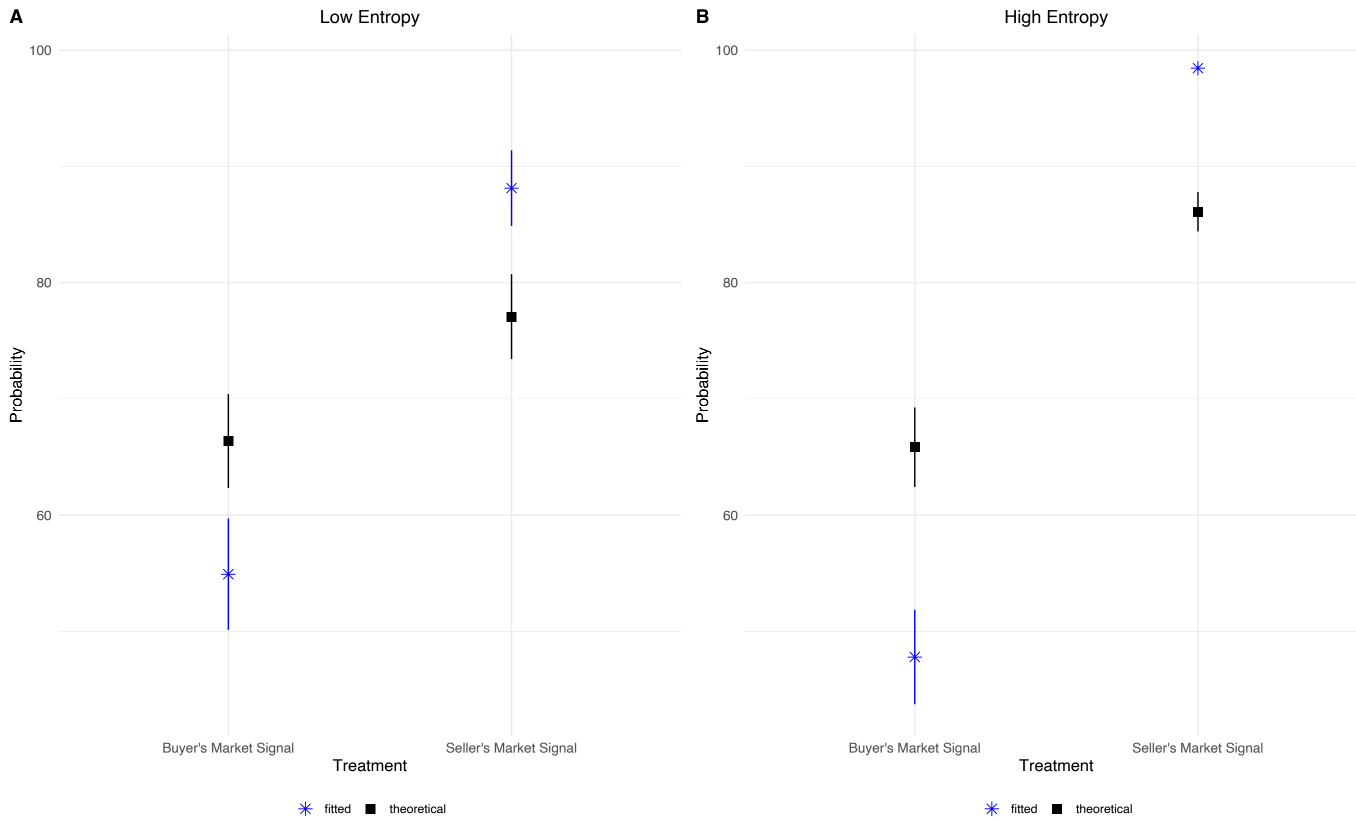
V.D Entropy and Belief Updating

Our model predicts that low cognitive cost will lead to optimistic belief updating. The model uses the inverse of entropy in prior beliefs as a proxy for the weight of cognitive cost. Figure S1 shows our model predictions for a relatively lower entropy level. Per Figure S1, low entropy increases the weight of cognitive cost in the utility function, reducing optimism in belief updating. This prediction can be observed by comparing the simulated biased posteriors in Figure 3 (with a higher entropy level) to those in Figure S1 (with a lower entropy level) for the case when $\phi = 0.7$. Put differently, when the decision-maker has high certainty (i.e., low entropy) in their prior beliefs, they are more likely to symmetrically react to signals. Having high certainty in prior beliefs increases the cognitive cost of holding biased posterior beliefs. Conversely, a reduction in belief certainty will trigger asymmetric and optimistic belief revision.

Figure 6 displays Bayesian belief analyses for low and high entropy sub-samples in the Main Study. We first calculate the entropy of allocated tokens to the prior intervals reflecting different year-over-year house price increase levels in August 2024. This allows us to measure the extent to which homeowners were certain in their prior beliefs about house price increases. Then, we split our sample based on the estimated median values of prior entropy. Finally, we estimate equation 3 for low and high prior belief entropy sub-samples.

We compare theoretical posteriors with fitted posteriors in Figure 6. We construct theoretical posteriors using priors and strict Bayesian belief updating. Fitted posteriors are obtained by i) first fitting equation 3 to our low- and high-entropy sub-samples and ii) constructing fitted posteriors using priors and estimated model parameters.

Figure 6 shows that, in the high-entropy sub-sample, homeowners exhibit higher over-reaction levels to both the Seller's and Buyer's Market Signal treatments than those in



Note: We compare fitted and theoretical posteriors in study treatments across low and high prior belief entropy sub-samples.

Figure 6: Prior Belief Entropy and Belief Updating in the Main Study.

the low-entropy sub-sample. A Chow test confirms that the low and high-entropy sub-samples are structurally different in terms of belief updating ($F\text{–}stat = 3.26$). We also find that the belief updating is symmetric in the low-entropy sub-sample ($\mathbb{P}(\beta_{\text{Seller's Market Signal}} = \beta_{\text{Buyer's Market Signal}} = 0.21)$). However, we detect asymmetric belief revision in the high-entropy sub-sample ($\mathbb{P}(\beta_{\text{Seller's Market Signal}} = \beta_{\text{Buyer's Market Signal}} < 0.01)$). Moreover, the fitted biased posteriors for the Seller's Market Signal treatment in the high-entropy sub-sample have a very tight confidence interval, and their mean is very close to 100%. We conclude that prior house price belief uncertainty can lead to asymmetric overreaction to information.[32]

[32]It is worth noting that belief updating has a non-linear nature. For instance, when the prior belief is 85%, a Bayesian thinker should revise their belief to the 93% (70%) posterior when the signal is positive (negative) and has a 71% accuracy. Thus, 8% upward and 15% downward belief revisions are symmetric with respect to the 85% prior. Moreover, strictly Bayesian updating magnitudes also change depending on the prior belief level. For instance, for a 60% prior belief, upward and downward symmetric belief revisions are 79% and 40%, respectively.

Table 5: Attention to Fed Meetings and Expected Mortgage Rate

	Following the Fed Meeting			
	(1)	(2)	(3)	(4)
Seller's Market Signal	−0.01		−0.01	−0.06*
	(0.03)		(0.03)	(0.03)
Republican		0.07**	0.07**	−0.02
		(0.03)	(0.03)	(0.04)
Seller's Market Signal*Republican				0.18***
				(0.06)
Constant	0.34***	0.31***	0.32***	0.34***
	(0.02)	(0.02)	(0.02)	(0.03)
N	1024	1024	1024	1024
Rsq	0.00	0.00	0.00	0.01

	Expected Mortgage Rate			
	(1)	(2)	(3)	(4)
Seller's Market Signal	0.10		0.11	0.12
	(0.08)		(0.08)	(0.10)
Republican		0.24***	0.25***	0.26**
		(0.09)	(0.09)	(0.13)
Seller's Market Signal*Republican				−0.03
				(0.18)
Constant	5.46***	5.44***	5.38***	5.37***
	(0.06)	(0.05)	(0.07)	(0.07)
N	1024	1024	1024	1024
Rsq	0.00	0.01	0.01	0.01

Note: This table shows the relationship between experimental treatment conditions of the Main Study and attention to the Fed's March 2024 meeting (upper panel) and expected mortgage rate (lower panel). We measured attention to the meeting and elicited expected mortgage rates in the Follow-up Study. We use OLS estimations. Robust HC1 standard errors are reported. *p<0.1; **p<0.05; ***p<0.01

V.E Attention to Fed Meetings and Expected Mortgage rates

We measure homeowners' attention to economic news containing any reference to Fed meetings in the Main and Follow-up Studies. We asked homeowners to indicate what recently caught their attention in the news and listed several non-exclusive options. We mentioned "Fed's meeting" along with other alternatives, such as "Stock Market Surge." We create a binary variable if a homeowner selects the “Fed’s meetin” alternative.

Table S6 shows that around 28% of homeowners mentioned being exposed to economic news with reference to Fed meetings in the Main Study. Partisanship does not have any effect on the reported attention to Fed meetings. Since this measure elicits attention to Fed meetings before our study treatments, we also do not detect any impact of Main Study treatments on our news attention measure.

Table 5 discusses homeowner attention to Fed meeting news in the Follow-up Study. Around 34% of homeowners indicate being exposed to Fed meeting news. We also find that Republican homeowners are 7 percentage points (p.p.) more likely to report paying attention to news pieces with reference to the Fed’s meeting compared to non-Republican participants. Table 5, column 4, shows that this effect is primarily driven by Republican homeowners who were exposed to the Seller’s Market Signal treatment in the Main Study.

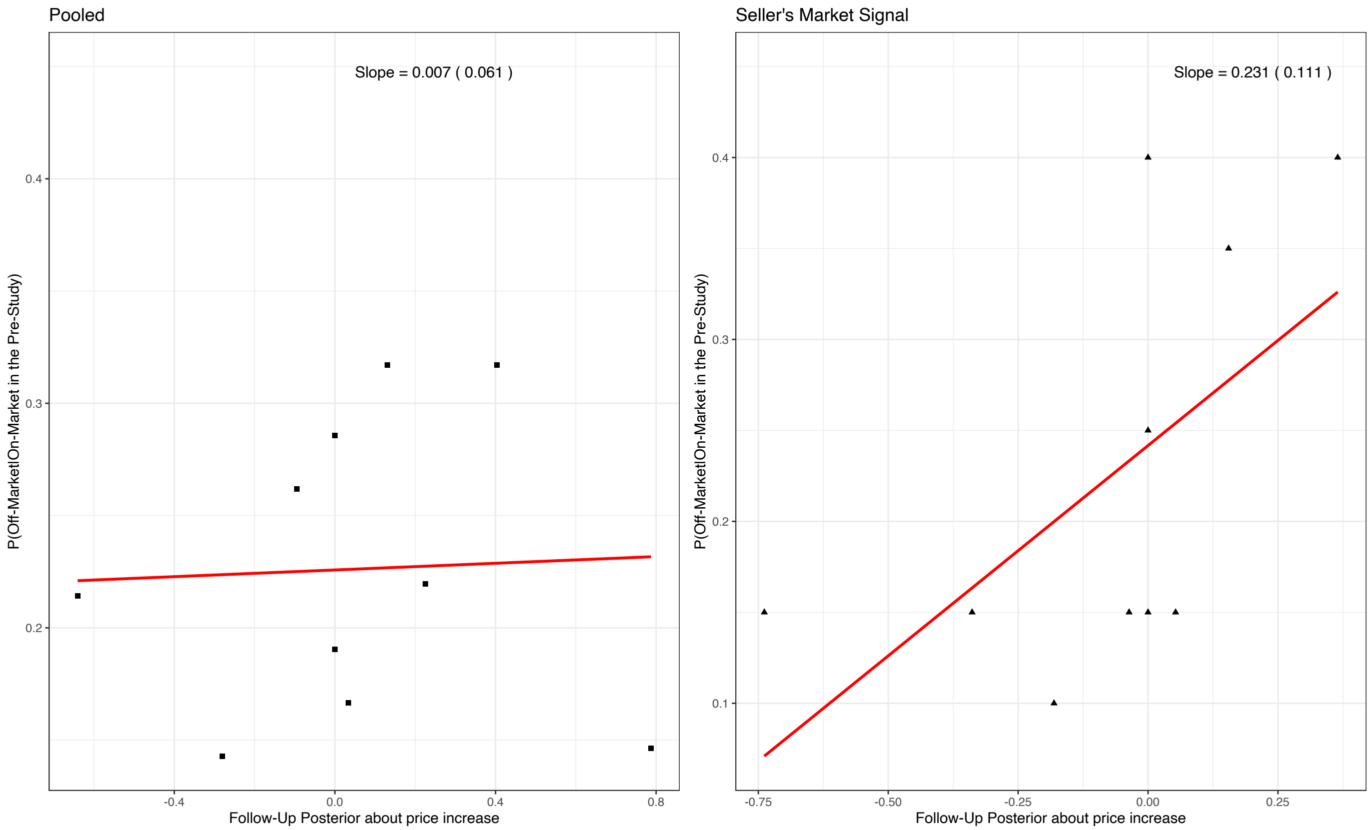
We also elicited expected mortgage rates by the end of the year in the Main and Follow-up Studies.[33] Table S6 shows that the average expected mortgage rate in the Main Study is around 5.30%. Additionally, being exposed to the Seller’s Market Signal increases the expected mortgage rate by approximately 0.49 percentage points (p.p.). Furthermore, Republican homeowners expect a 0.29 p.p. higher rate than non-Republican homeowners.

Table 5 shows that, in the Follow-up Study, the average expected mortgage rate increased to 5.46%. We do not detect any effect of our Main Study treatments on the expected mortgage rate level in the Follow-up Study. However, Republican homeowners continue to expect a higher mortgage rate, by around 0.24 p.p., compared to non-Republican participants.

V.F Belief Updates and Willingness to Sell

Finally, we analyze to what extent belief revisions affect Willingness to Sell (WTS). We elicit probabilistic WTS in the Pre- and Follow-up Studies. We create a dummy variable using Pre-Study responses to classify homeowners as “On-Market” if they indicate a positive

[33] We measured expected mortgage rates by asking homeowners to select the interval they believed would contain the average mortgage rate by the end of 2024. We included eight intervals ranging from “Less than 2%” to “8% or more.” Responses were coded by the middle points of the intervals, using 1.5% and 8.5% for the “Less than 2%” and “8% or more” intervals, respectively.



Note: We analyze how On-Market homeowners' market exit probabilities in the Follow-up Study are affected by being exposed to the Seller's Market treatment in the Main Study. We restrict our analyses to On-Market homeowners (based on WTS in the Pre-Study). Binned scatter plots of fitted probabilities are displayed.

Figure 7: On-Market Homeowners' Belief Updating and Willingness to Sell in the Follow-up Study.

probability of considering selling their property; otherwise, we categorize homeowners as "Off-Market." We repeat this measure in the Follow-up Study.

We find that, in the Follow-up Study, around 21% of Off-Market homeowners exhibit a non-zero WTS and indicate considering selling their properties by the end of the year. Conversely, approximately 23% of On-Market homeowners exit the market, indicating 0 WTS. Fisher's exact test shows that the proportion of homeowners exiting the market is not different (p-value $= 0.57$) than the share of homeowners willing to enter the market.

We also analyze the determinants of market exit decisions in the Follow-up sample among On-Market homeowners. Figure 7 shows that an increase in Follow-up posterior belief (with respect to the Main Study posterior) about a house price increase also increases the probability of exiting the market in the On-Market sub-sample. Table S7 provides regression analyses showing that this effect is driven by On-Market homeowners who were exposed to the Seller's Market Signal information treatment in the Main Study. Specifically, a 10 p.p. increase in Follow-up posteriors about the probability of experiencing a house price increase in one's zip code also increases the market exit probability by 3 p.p.

VI Conclusion

Despite the housing market's crucial role in the economy, little is known about the behavioral factors affecting housing price dynamics (Manski, 2004). Recent studies have shed light on behavioral biases influencing house prices (Armona et al., 2019; Fuster et al., 2022; Chopra et al., 2023; Binder et al., 2023; Bottan and Perez-Truglia, 2020; Bailey et al., 2019); however, there is a need to connect documented behaviors to cognitive models and comprehensively map the fundamentals of housing price expectations (Kuchler et al., 2023). Directly eliciting economic expectations with survey experiments has several advantages, such as not relying on strong assumptions about preferences (Kuchler et al., 2023) and identifying cognitive mechanisms of the economic decision-making process (Manski, 2004). Moreover, after the 2008 Great Recession, housing price dynamics began exhibiting a stronger correlation with financial markets (Leung, 2023), suggesting that homes are increasingly becoming investment vehicles for households (Duca et al., 2019). This paper uses recent developments in behavioral finance to investigate the cognitive mechanisms behind house price dynamics.

Specifically, we study how homeowners form and update their house price expectations. We use a series of incentivized studies to measure house price belief updates in response to our optimistic (suggesting a seller's market) and pessimistic (forecasting a buyer's market) macroeconomic predictions. We connect the house price expectation formation process to a rich set of controls, such as Willingness to Sell (WTS), property value, and the zip code's last 12 and 36-month house price growth history.

Our studies are deliberately designed to elicit homeowners' behaviors on the day after the Federal Reserve's (Fed) first and second meetings of the year. We explore the market uncertainty about the Fed's decision to either maintain its policy rate at a historically high level to control rising CPI rates or to reduce interest rates to avoid the likelihood of an economic "hard landing" (Blinder, 2023). Our designed optimistic and pessimistic macroeconomic predictions reflected the primary market forecasts at the time of our study, which were almost equally likely. Thus, we investigate the cognitive micro-foundations of house price expectations when homeowners are exposed to optimistic or pessimistic information treatments.

We find that homeowners overreact to our optimistic and pessimistic information treatments; however, the magnitude of the belief revision is higher for the optimistic prediction. This result aligns with recent studies documenting overreaction to macroeconomic indicators in financial markets (Bordalo et al., 2020; Barberis, 2018). We also document that homeowners' optimistic overreaction to information is mediated by property value and experienced recent price growth. Specifically, homeowners with relatively lower-valued properties are more prone to optimism bias. Similar effects are detected for homeowners living in zip codes with relatively lower recent price growth trends. To explain these findings, we develop a modeling framework that integrates Bayesian belief revision biases into Motivated Belief models (Möbius et al., 2022).

We also find a significant revision to house price expectations in the Follow-up study, indicating that homeowners actively monitor macroeconomic changes. There is an approximately six percentage point increase in reported news exposure related to Fed meetings, suggesting that our information treatments nudged homeowners to be more attentive to monetary policy. An upward revision in the house price increase probability leads to a reduction in Willingness to Sell (WTS). This finding highlights the role of house price expectations in housing inventory supply. Additionally, we detect that Republicans are more likely to expect higher mortgage rates than non-Republican homeowners, demonstrating the role of partisanship in shaping macroeconomic expectations.

Future work might explore how homeowners' house price expectations are related to their active financial investment portfolios. Increasingly available financial lending options based on home equities might induce highly leveraged debt positions (Duca et al., 2019). This could also introduce more frequent financial market shocks to the housing market. Moreover, as households become more active in retail investments, they may increasingly apply financial market logic to their house price expectations. This necessitates investigating house price expectations through the lens of behavioral finance (Barberis, 2018).

References

Adam, K. and Nagel, S. (2023). Expectations data in asset pricing. In *Handbook of Economic Expectations*, pages 477–506. Elsevier.

Agranov, M. and Ortoleva, P. (2017). Stochastic choice and preferences for randomization. *Journal of Political Economy*, 125(1):40–68.

Armantier, O., Bruine de Bruin, W., Potter, S., Topa, G., Van Der Klaauw, W., and Zafar, B. (2013). Measuring inflation expectations. *Annual Revue of Econonomics*, 5(1):273–301.

Armona, L., Fuster, A., and Zafar, B. (2019). Home price expectations and behaviour: Evidence from a randomized information experiment. *The Review of Economic Studies*, 86(4):1371–1410.

Augenblick, N., Lazarus, E., and Thaler, M. (2023). Overinference from weak signals and underinference from strong signals.

Ba, C., Bohren, J. A., and Imas, A. (2022). Over-and underreaction to information. *Available at SSRN 4274617*.

Bailey, M., Dávila, E., Kuchler, T., and Stroebel, J. (2019). House price beliefs and mortgage leverage choice. *The Review of Economic Studies*, 86(6):2403–2452.

Barberis, N. (2018). Psychology-based models of asset prices and trading volume. In *Handbook of Behavioral Economics: Applications and Foundations 1*, volume 1, pages 79–175. Elsevier.

Barberis, N., Greenwood, R., Jin, L., and Shleifer, A. (2018). Extrapolation and bubbles. *Journal of Financial Economics*, 129(2):203–227.

Barberis, N., Shleifer, A., and Vishny, R. (1998). A model of investor sentiment. *Journal of financial economics*, 49(3):307–343.

Bénabou, R. and Tirole, J. (2002). Self-confidence and personal motivation. *The quarterly journal of economics*, 117(3):871–915.

Bénabou, R. and Tirole, J. (2016). Mindful economics: The production, consumption, and value of beliefs. *Journal of Economic Perspectives*, 30(3):141–164.

Benjamin, D. J. (2019). Errors in probabilistic reasoning and judgment biases. *Handbook of Behavioral Economics: Applications and Foundations 1*, 2:69–186.

Binder, C., Kuang, P., and Tang, L. (2023). Central bank communication and house price expectations. Technical report, National Bureau of Economic Research.

Blinder, A. S. (2023). Landings, soft and hard: The federal reserve, 1965–2022. *Journal of Economic Perspectives*, 37(1):101–120.

Bordalo, P., Gennaioli, N., Ma, Y., and Shleifer, A. (2020). Overreaction in macroeconomic expectations. *American Economic Review*, 110(9):2748–2782.

Bottan, N. L. and Perez-Truglia, R. (2020). Betting on the house: Subjective expectations and market choices. Technical report, National Bureau of Economic Research.

Case, K. E. and Shiller, R. J. (1988). The efficiency of the market for single-family homes.

Case, K. E. and Shiller, R. J. (1990). Forecasting prices and excess returns in the housing market. *Real Estate Economics*, 18(3):253–273.

Case, K. E., Shiller, R. J., and Thompson, A. (2012). What have they been thinking? home buyer behavior in hot and cold markets. Technical report, National Bureau of Economic Research.

Chopra, F., Roth, C., and Wohlfart, J. (2023). Home price expectations and spending: Evidence from a field experiment. *Available at SSRN 4452588*.

Cutler, D. M., Poterba, J. M., and Summers, L. H. (1991). Speculative dynamics. *The Review of Economic Studies*, 58(3):529–546.

de Bruin, W. B., Chin, A., Dominitz, J., and van der Klaauw, W. (2023). Household surveys and probabilistic questions. In *Handbook of Economic Expectations*, pages 3–31. Elsevier.

Drobner, C. and Goerg, S. J. (2024). Motivated belief updating and rationalization of information. *Management Science*.

Duca, J. V., Popoyan, L., and Wachter, S. M. (2019). Real estate and the great crisis: Lessons for macroprudential policy. *Contemporary Economic Policy*, 37(1):121–137.

Eggleston, J., Hays, D., Munk, R., and Sullivan, B. (2020). *The Wealth of Households, 2017*. US Department of Commerce, US Census Bureau Washington, DC, USA.

Engelhardt, G. V. (1994). House prices and the decision to save for down payments. *Journal of Urban Economics*, 36(2):209–237.

Engelmann, J. B., Lebreton, M., Salem-Garcia, N. A., Schwardmann, P., and van der Weele, J. J. (2024). Anticipatory anxiety and wishful thinking. *American Economic Review*, 114(4):926–960.

Exley, C. L. and Nielsen, K. (2024). The gender gap in confidence: Expected but not accounted for. *American Economic Review*, 114(3):851–885.

FRED (2024). S&P Case-Shiller U.S. National Home Price Index. Accessed: 2024-05-25.

Fuster, A., Perez-Truglia, R., Wiederholt, M., and Zafar, B. (2022). Expectations with endogenous information acquisition: An experimental investigation. *Review of Economics and Statistics*, 104(5):1059–1078.

Glaeser, E. L., Gyourko, J., Morales, E., and Nathanson, C. G. (2014). Housing dynamics: An urban approach. *Journal of Urban Economics*, 81:45–56.

Glaeser, E. L. and Nathanson, C. G. (2017). An extrapolative model of house price dynamics. *Journal of Financial Economics*, 126(1):147–170.

Greene, W. H. (2003). *Econometric analysis*. Prentice Hall.

Greenwood, R. and Shleifer, A. (2014). Expectations of returns and expected returns. *The Review of Financial Studies*, 27(3):714–746.

Grether, D. M. (1980). Bayes rule as a descriptive model: The representativeness heuristic. *The Quarterly journal of economics*, 95(3):537–557.

Haaland, I., Roth, C., and Wohlfart, J. (2023). Designing information provision experiments. *Journal of economic literature*, 61(1):3–40.

Kaplan, G. and Violante, G. L. (2018). Microeconomic heterogeneity and macroeconomic shocks. *Journal of Economic Perspectives*, 32(3):167–194.

Kuchler, T., Piazzesi, M., and Stroebel, J. (2023). Housing market expectations. In *Handbook of Economic Expectations*, pages 163–191. Elsevier.

Lee, W. S. and Ma, E. (2023). Housing market connectedness and transmission of monetary policy. *Available at SSRN 4451791*.

Leung, C. K. (2023). Housing and macroeconomics. *Available at SSRN 4345896*.

Leung, C. K. Y. and Ng, C. Y. J. (2019). Macroeconomic aspects of housing. In *Oxford Research Encyclopedia of Economics and Finance*.

Maćkowiak, B., Matějka, F., and Wiederholt, M. (2023). Rational inattention: A review. *Journal of Economic Literature*, 61(1):226–273.

Manski, C. F. (2004). Measuring expectations. *Econometrica*, 72(5):1329–1376.

Mishkin, F. S. (2007). Housing and the monetary transmission mechanism.

Möbius, M. M., Niederle, M., Niehaus, P., and Rosenblat, T. S. (2022). Managing self-confidence: Theory and experimental evidence. *Management Science*, 68(11):7793–7817.

Qian, H. (2009). Time variation in analyst optimism: An investor sentiment explanation. *The Journal of Behavioral Finance*, 10(3):182–193.

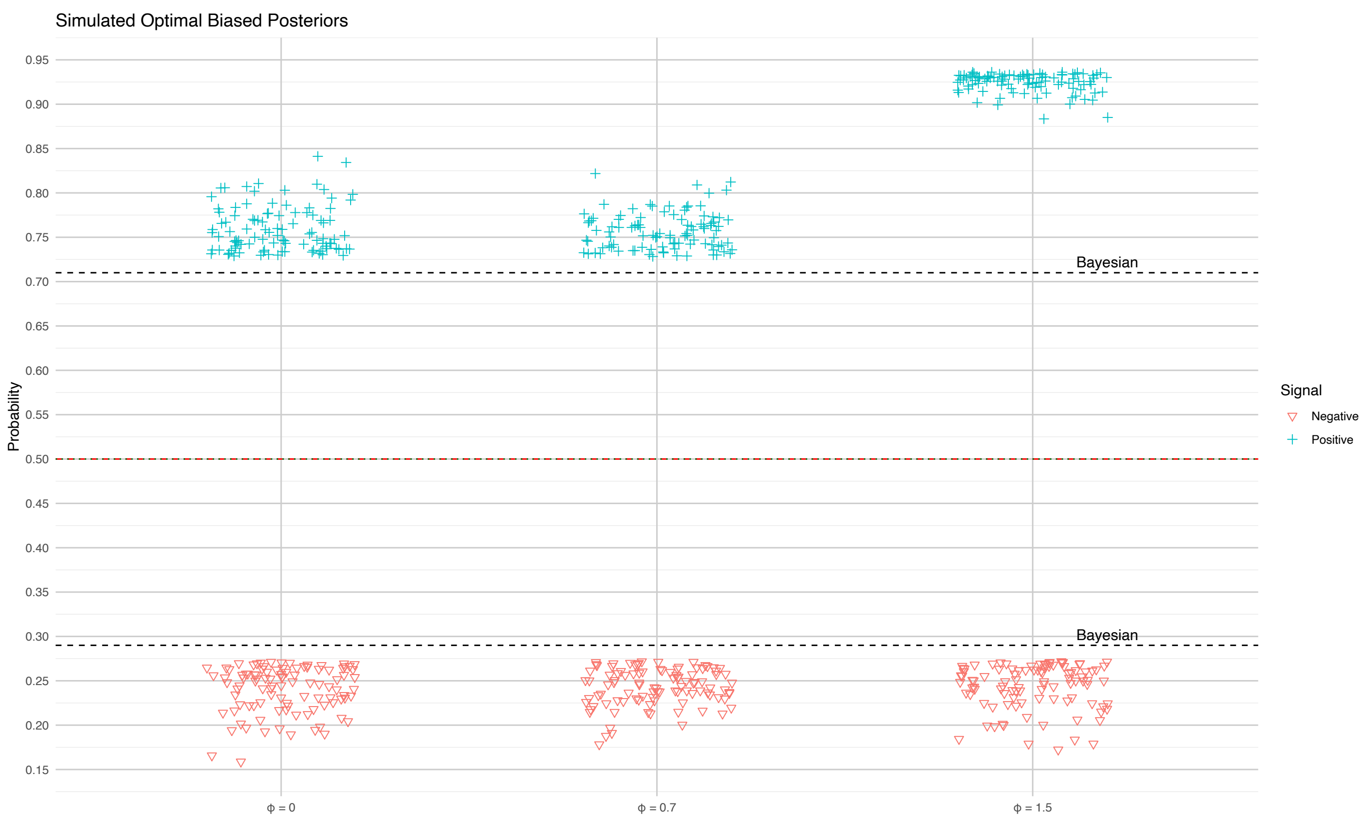
Roth, C. and Wohlfart, J. (2020). How do expectations about the macroeconomy affect personal expectations and behavior? *Review of Economics and Statistics*, 102(4):731–748.

Shiller, R. J. (2007). Understanding recent trends in house prices and home ownership.

Skinner, D. J. and Sloan, R. G. (2002). Earnings surprises, growth expectations, and stock returns or don't let an earnings torpedo sink your portfolio. *Review of accounting studies*, 7(2):289–312.

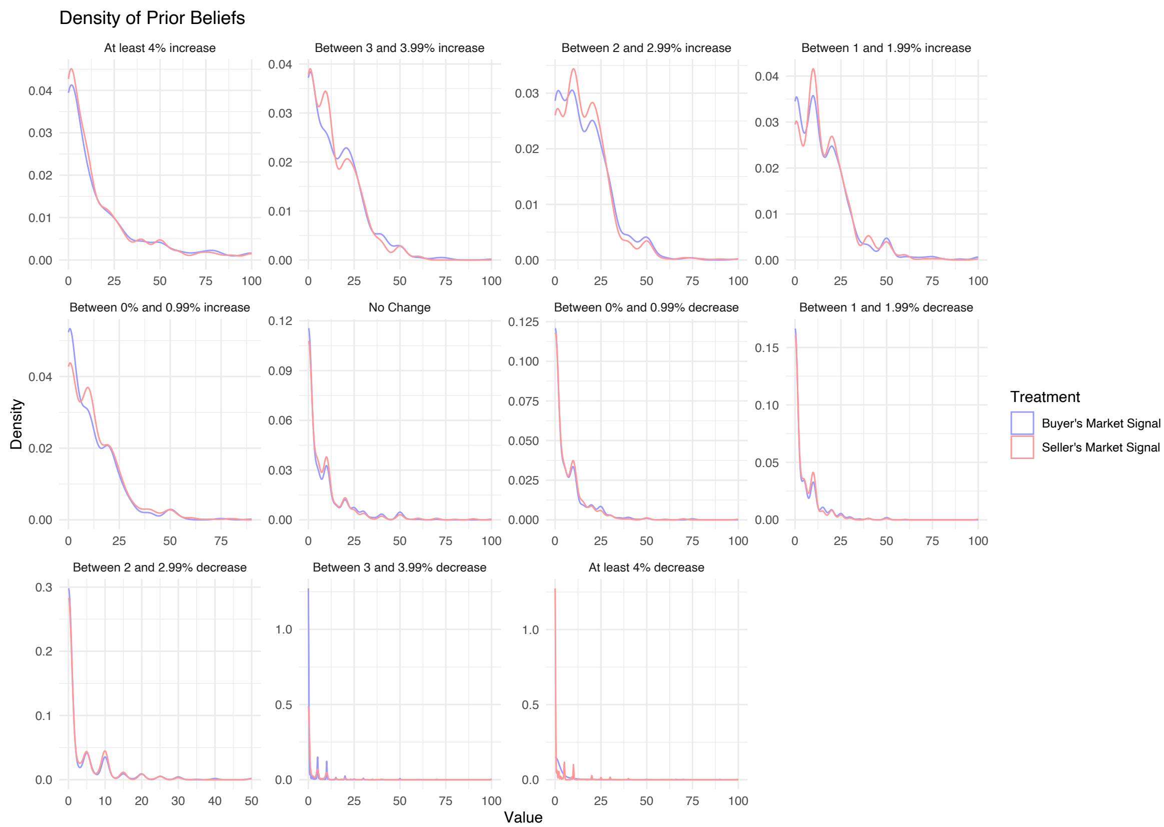
Stantcheva, S. (2023). How to run surveys: A guide to creating your own identifying variation and revealing the invisible. *Annual Review of Economics*, 15:205–234.

Appendix

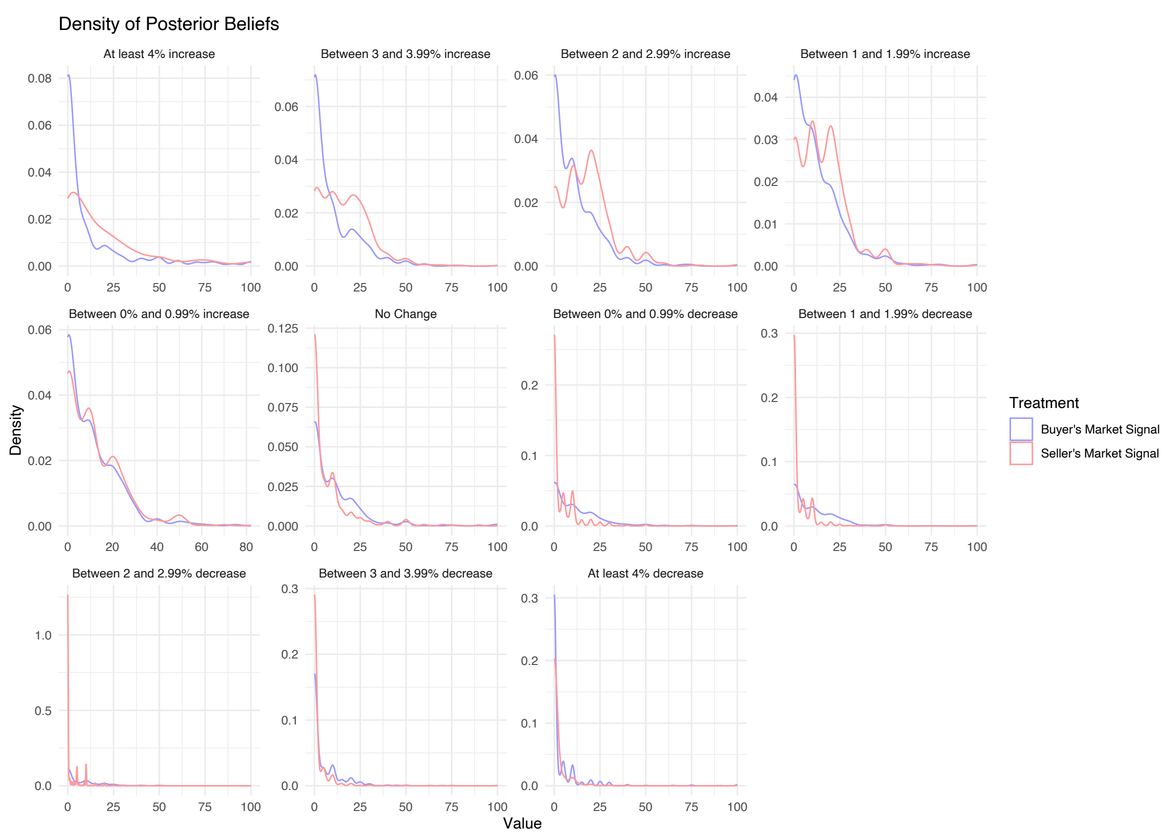


Note: We compare simulated biased posteriors across positive and negative signals. We set $\psi = 0.5$ (i.e., a relatively lower prior belief entropy level compared to the case in Figure 3.). Each cluster holds 100 biased posteriors. We set the true and prior probabilities to 0.5 to reflect the macroeconomic environment in our Main study. M is normalized to 1 in simulations.

Figure S1: Simulated Biased Posteriors and Optimism Bias.



[A]



[B]

Note: This figure shows the densities of prior and posterior beliefs for each house price change interval.

Figure S2: Density of Prior and Posterior Beliefs (Main Study)

Table S1: The Comparison of Primary Household Characteristics (Pre-study vs. Main Study)

	Pre-study vs. Main Study				
	N	Only Pre-study (N = 1,074)	Both Pre-study and Main Study (N = 1,415)	p-value	Adj. p-value
On-Market	2,489	417 (39%)	585 (41%)	0.20	0.48
House	2,489	1,008 (94%)	1,302 (92%)	0.08	0.43
Apartment	2,489	24 (2.2%)	46 (3.3%)	0.13	0.43
Mobile home	2,489	39 (3.6%)	56 (4.0%)	0.67	0.77
Other type of property	2,489	3 (0.3%)	11 (0.8%)	0.10	0.43
Rents/Airbnb	2,489	28 (2.6%)	49 (3.5%)	0.22	0.48
Urban	2,489	799 (74%)	1,036 (73%)	0.51	0.72
Mortgage (No)	2,489	278 (26%)	469 (33%)	0.00	0.00
Mortgage (less than 2.50%)	2,489	149 (10%)	81 (8.1%)	0.10	0.36
Mortgage (between 2.50% and 2.99)	2,489	198 (18%)	234 (17%)	0.22	0.48
Mortgage (between 3.00% and 3.49%)	2,489	191 (18%)	213 (15%)	0.07	0.43
Mortgage (between 3.50% and 3.99%)	2,489	99 (9.2%)	115 (8.1%)	0.34	0.58
Mortgage (between 4.00% and 4.49%)	2,489	87 (8.1%)	92 (6.5%)	0.13	0.43
Mortgage (between 4.50% and 4.99%)	2,489	26 (2.4%)	25 (1.8%)	0.25	0.49
Mortgage (between 5.00% and 5.49%)	2,489	31 (2.9%)	56 (4.0%)	0.15	0.43
Mortgage (between 5.50% and 5.99%)	2,489	12 (1.1%)	20 (1.4%)	0.52	0.72
Mortgage (between 6.00% and 6.49%)	2,489	23 (2.1%)	27 (1.9%)	0.68	0.77
Mortgage (between 6.50% and 6.99%)	2,489	14 (1.3%)	19 (1.3%)	0.93	0.93
Mortgage (7.00% or more)	2,489	15 (1.4%)	15 (1.1%)	0.45	0.68
Market Value: Less than $150,000	2,489	126 (12%)	146 (10%)	0.26	0.49
Market Value: Between $150,000 and $299,999	2,489	310 (29%)	395 (28%)	0.60	0.76
Market Value: Between $300,000 and $449,999	2,489	290 (27%)	351 (25%)	0.21	0.48
Market Value: Between $450,000 and $599,999	2,489	148 (14%)	225 (16%)	0.14	0.43
Market Value: Between $600,000 and $749,999	2,489	95 (8.8%)	140 (9.9%)	0.38	0.62
Market Value: Between $750,000 and $899,999	2,489	45 (4.2%)	56 (4.0%)	0.77	0.85
Market Value: $900,000 or more	2,489	60 (5.6%)	102 (7.2%)	0.10	0.43
N bedrooms: 1	2,489	6 (0.6%)	28 (2.0%)	0.00	0.05
N bedrooms: 2	2,489	100 (9.3%)	178 (13%)	0.01	0.15
N bedrooms: 3	2,489	546 (51%)	654 (46%)	0.02	0.19
N bedrooms: 4	2,489	340 (32%)	429 (30%)	0.47	0.70
N bedrooms: 5 or more	2,489	82 (7.6%)	126 (8.9%)	0.26	0.49
SQFT: less than 1,000 sqft	2,489	44 (4.1%)	65 (4.6%)	0.55	0.74
SQFT: Between 1,000 and 1,999 sqft	2,489	535 (50%)	660 (47%)	0.12	0.43
SQFT: Between 2,000 and 2,999 sqft	2,489	350 (33%)	496 (35%)	0.20	0.48
SQFT: 3,000 sqft or more	2,489	145 (14%)	194 (14%)	0.88	0.92
Household Income: Less than $50,000	2,489	159 (15%)	219 (15%)	0.64	0.77
Household Income: Between $50,000 and $74,999	2,489	206 (19%)	259 (18%)	0.58	0.75
Household Income: Between $75,000 and $99,999	2,489	175 (16%)	253 (18%)	0.30	0.54
Household Income: Between $100,000 and $124,999	2,489	147 (14%)	177 (13%)	0.39	0.62
Household Income: Between $125,00 and $149,999	2,489	141 (13%)	195 (14%)	0.64	0.77
Household Income: Between $150,000 and $174,999	2,489	67 (6.2%)	110 (7.8%)	0.14	0.43
Household Income: Between $175,000 and $199,999	2,489	65 (6.1%)	56 (4.0%)	0.02	0.17
Household Income: $200,000 or more	2,489	114 (11%)	146 (10%)	0.81	0.87

Note: The table shows the primary demographic characteristics of recruited households. Reported statistics is n (%), i.e., counts and proportions. We conducted Pearson's Chi-squared test to compare proportions across groups. Benjamini & Hochberg correction for multiple testing was applied in computing Adj. p-values.

Table S2: The Comparison of Primary Household Characteristics across Main Study Treatments

	Buyer's Market Signal vs. Seller's Market Signal				
	N	Buyer's Market Signal (N = 708)	Seller's Market Signal (N = 707)	p-value	Adj. p-value
On-Market	1,415	292 (41%)	293 (41%)	0.94	0.96
House	1,415	665 (94%)	637 (90%)	0.01	0.17
Apartment	1,415	13 (1.8%)	33 (4.7%)	0.00	0.12
Mobile home	1,415	23 (3.2%)	33 (4.7%)	0.17	0.63
Other type of property	1,415	7 (1.0%)	4 (0.6%)	0.37	0.79
Rents/Airbnb	1,415	25 (3.5%)	24 (3.4%)	0.89	0.93
Urban	1,415	530 (75%)	506 (72%)	0.16	0.63
Mortgage (No)	1,415	238 (34%)	231 (33%)	0.71	0.86
Mortgage (less than 2.50%)	1,415	67 (9.5%)	63 (8.9%)	0.72	0.86
Mortgage (between 2.50% and 2.99)	1,415	105 (15%)	129 (18%)	0.08	0.60
Mortgage (between 3.00% and 3.49%)	1,415	111 (16%)	102 (14%)	0.51	0.79
Mortgage (between 3.50% and 3.99%)	1,415	54 (7.6%)	61 (8.6%)	0.49	0.79
Mortgage (between 4.00% and 4.49%)	1,415	37 (5.2%)	55 (7.8%)	0.05	0.44
Mortgage (between 4.50% and 4.99%)	1,415	16 (2.3%)	9 (1.3%)	0.16	0.63
Mortgage (between 5.00% and 5.49%)	1,415	34 (4.8%)	22 (3.1%)	0.10	0.63
Mortgage (between 5.50% and 5.99%)	1,415	9 (1.3%)	11 (1.6%)	0.65	0.86
Mortgage (between 6.00% and 6.49%)	1,415	17 (2.4%)	10 (1.4%)	0.17	0.63
Mortgage (between 6.50% and 6.99%)	1,415	8 (1.1%)	11 (1.6%)	0.49	0.79
Mortgage (7.00% or more)	1,415	12 (1.7%)	3 (0.4%)	0.02	0.28
Market Value: Less than $150,000	1,415	68 (9.6%)	78 (11%)	0.38	0.79
Market Value: Between $150,000 and $299,999	1,415	200 (28%)	195 (28%)	0.78	0.88
Market Value: Between $300,000 and $449,999	1,415	178 (25%)	173 (24%)	0.77	0.88
Market Value: Between $450,000 and $599,999	1,415	108 (15%)	117 (17%)	0.51	0.79
Market Value: Between $600,000 and $749,999	1,415	76 (11%)	64 (9.1%)	0.29	0.79
Market Value: Between $750,000 and $899,999	1,415	28 (4.0%)	28 (4.0%)	1.00	1.00
Market Value: $900,000 or more	1,415	50 (7.1%)	52 (7.4%)	0.83	0.91
N bedrooms: 1	1,415	12 (1.7%)	16 (2.3%)	0.44	0.79
N bedrooms: 2	1,415	85 (12%)	93 (13%)	0.51	0.79
N bedrooms: 3	1,415	335 (47%)	319 (45%)	0.41	0.79
N bedrooms: 4	1,415	211 (30%)	218 (31%)	0.67	0.86
N bedrooms: 5 or more	1,415	65 (9.2%)	61 (8.6%)	0.72	0.86
SQFT: less than 1,000 sqft	1,415	34 (4.8%)	31 (4.4%)	0.71	0.86
SQFT: Between 1,000 and 1,999 sqft	1,415	338 (48%)	322 (46%)	0.41	0.79
SQFT: Between 2,000 and 2,999 sqft	1,415	242 (34%)	254 (36%)	0.49	0.79
SQFT: 3,000 sqft or more	1,415	94 (13%)	100 (14%)	0.64	0.86
Household Income: Less than $50,000	1,415	118 (17%)	101 (14%)	0.22	0.71
Household Income: Between $50,000 and $74,999	1,415	124 (18%)	135 (19%)	0.44	0.79
Household Income: Between $75,000 and $99,999	1,415	128 (18%)	125 (18%)	0.84	0.91
Household Income: Between $100,000 and $124,999	1,415	86 (12%)	91 (13%)	0.68	0.86
Household Income: Between $125,00 and $149,999	1,415	112 (16%)	83 (12%)	0.03	0.28
Household Income: Between $150,000 and $174,999	1,415	50 (7.1%)	60 (8.5%)	0.32	0.79
Household Income: Between $175,000 and $199,999	1,415	25 (3.5%)	31 (4.4%)	0.41	0.79
Household Income: $200,000 or more	1,415	65 (9.2%)	81 (11%)	0.16	0.63

Note: The table shows the primary demographic characteristics of recruited households. Reported statistics is n (%), i.e., counts and proportions. We conducted Pearson's Chi-squared test to compare proportions across groups. Benjamini & Hochberg correction for multiple testing was applied in computing Adj. p-values.

Table S3: Manipulation Checks for Main Study Experimental Treatment Conditions (Follow-up Study)

	(1)	(2)	(3)	(4)	(5)	(6)
Seller's Market Signal	0.08^{***}	0.02	-0.01	-0.01	-0.05^{*}	-0.07^{**}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Constant	0.58^{***}	0.22^{***}	0.42^{***}	0.59^{***}	0.54^{***}	0.44^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	1024	1024	1024	1024	1024	1024
Rsq	0.01	0.00	0.00	0.00	0.00	0.00

Note: This table presents manipulation checks for the Seller's Market Signal and Buyer's Market Signal experimental conditions in the follow-up study. OLS regression coefficients and robust HC1 standard errors are reported. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Primary Measure: In column (1), the dependent variable was constructed using two survey questions that independently elicited respondents' opinions about general market conditions for selling and buying a house. A 5-point Likert scale was used, ranging from "A very bad time" to "A very good time," with a midpoint of "Neither a good time nor bad time." The dependent variable was coded as 1 if the respondent indicated a relatively better time to sell a house than to buy one. The "Unsure/No opinion" option was also provided.

Other potential channels: Columns (2)-(3) display the influence of the treatment conditions on six-month-ahead expectations regarding employment and economic growth, respectively. A 5-point Likert scale was used, ranging from "Will significantly decrease" to "Will significantly increase," with a midpoint of "Will remain about the same." The "Unsure/No opinion" option was also provided. The dependent variable was coded as 1 if the respondent indicated either "Will significantly increase" or "Will somewhat increase."

Columns (4)-(7) show the relationship between the treatments and six-month-ahead optimism about personal finance, the financial prospects of people living in the same zip code, and the United States, respectively. A 5-point Likert scale was used, ranging from "Very pessimistic" to "Very optimistic," with a midpoint of "Neutral." The "Not sure/No opinion" option was also provided. The dependent variable was coded as 1 if the respondent indicated either "Somewhat optimistic" or "Very optimistic."

Table S4: Determinants of Housing Price Priors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Seller's Market Signal	−0.15						
	(1.61)						
On-Market		−1.47					
		(1.64)					
Experienced low 12-month price growth			−4.43***				
			(1.63)				
Experienced low 36-month price growth				−2.20			
				(1.63)			
Republican					−1.10		
					(1.76)		
Market value of owned house (USD/sqft)						0.01**	
						(0.01)	
Adj. income							1.30***
							(0.33)
Constant	73.11***	73.64***	75.49***	74.37***	73.36***	70.07***	68.16***
	(1.16)	(1.05)	(1.14)	(1.14)	(0.96)	(1.49)	(1.52)
N	1415	1415	1386	1386	1415	1415	1415
Rsq	0.00	0.00	0.01	0.00	0.00	0.00	0.01

Note: This table provides analyses on determining the primary determinants of housing price expectation priors. The dependent variable is the total percentage points allocated to house price growth intervals for participants' zip codes. Specifically, we combined allocated percentage points to 0.01% − 0.99%, 1% − 1.99%, 2% − 2.99%, 3% − 3.99%, and At least 4% for August 2024 year-over-year house price growth intervals.

"On Market" is a dummy variable indicating homeowners considering selling their properties in 2024.

"Experienced low short-term growth" was calculated using Zillow's 2023 monthly Home Value Indices (HVI) for participants' zip codes. We estimated the slope of HVI over 12 months for each zip code. Then, we split the estimated HVI slope distribution at the median point. "Experienced low short-term growth" is a dummy variable indicating a relatively low growth in house prices during the previous 12 months. Zillow did not have historical market prices for 29 zip codes.

"Experienced low medium-term growth" was calculated using Zillow's 2021-2023 monthly Home Value Indices (HVI) for participants' zip codes. We estimated the slope of HVI over 36 months for each zip code. Then, we split the estimated HVI slope distribution at the median point. "Experienced low medium-term growth" is a dummy variable indicating a relatively low growth in house prices during the previous 36 months. Zillow did not have historical market prices for 29 zip codes.

Republican is a dummy variable indicating if a respondent favors (leans towards, weakly or strongly) the Republican Party.

"Market value of owned house" was constructed with the reported market value of the owned property divided by the reported square footage of the house.

"Adjusted Income" was constructed by dividing the reported household income by the number of people in the household.

OLS regression coefficients and robust HC1 standard errors are reported.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table S5: Bayesian Updating and Partisanship
(Main Study)

	Belief updating about House Price Increase		
	Pooled	*Republican*	*Non-Republican*
	(1)	(2)	(3)
$\boldsymbol{\delta}$	0.72***	0.69***	0.73***
	(0.02)	(0.04)	(0.03)
$\boldsymbol{\beta}_{\text{Seller's Market Signal}}$	3.76***	4.01***	3.65***
	(0.22)	(0.43)	(0.26)
$\boldsymbol{\beta}_{\text{Buyer's Market Signal}}$	2.76***	2.80***	2.74***
	(0.21)	(0.38)	(0.25)
N	1269	380	889
Rsq	0.64	0.60	0.65
Chow Test for sub-sample models:	$F - stat = 0.42$ *p-value*= 0.74		

Note: This table presents structural Bayesian analyses for the entire sample of homeowners and sub-samples. The dependent variable is the posterior odd ratio for logit beliefs. The variable δ shows the prior odd ratio for logit beliefs. Robust HC1 standard errors and OLS estimates are reported. *p<0.1; **p<0.05; ***p<0.01

Table S6: Attention to Fed Meetings and Expected Mortgage Rate

	Following the Fed Meeting			
	(1)	(2)	(3)	(4)
Seller's Market Signal	0.02		0.02	0.02
	(0.02)		(0.02)	(0.03)
Republican		−0.01	−0.01	−0.01
		(0.03)	(0.03)	(0.04)
Seller's Market Signal*Republican				0.001
				(0.05)
Constant	0.28***	0.29***	0.29***	0.29***
	(0.02)	(0.01)	(0.02)	(0.02)
N	1415	1415	1415	1415
Rsq	0.00	0.00	0.00	0.00

	Expected Mortgage Rate			
	(1)	(2)	(3)	(4)
Seller's Market Signal	0.43***		0.44***	0.45***
	(0.07)		(0.07)	(0.09)
Republican		0.24***	0.26***	0.29**
		(0.08)	(0.08)	(0.11)
Seller's Market Signal*Republican				−0.05
				(0.16)
Constant	5.09***	5.23***	5.01***	5.00***
	(0.05)	(0.04)	(0.06)	(0.06)
N	1415	1415	1415	1415
Rsq	0.02	0.01	0.03	0.03

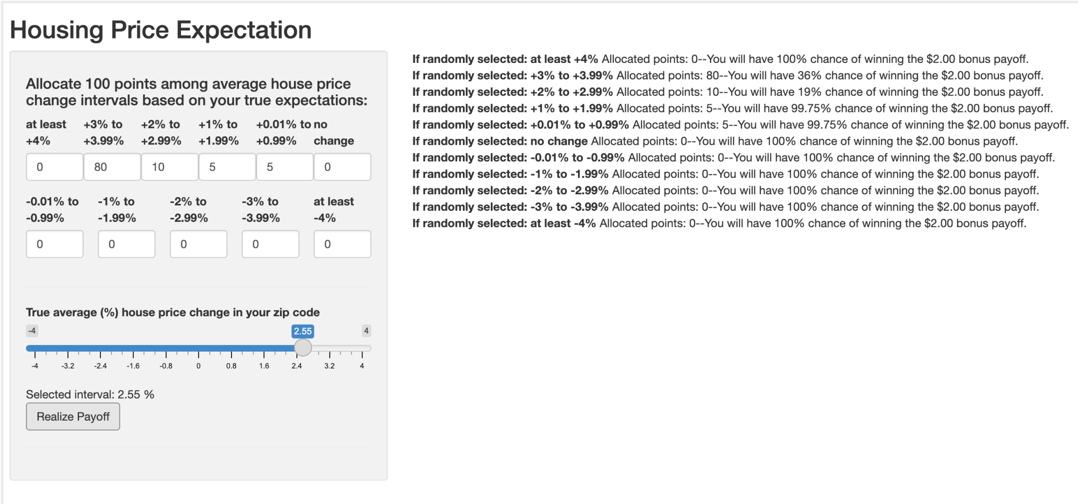
Note: This table shows the relationship between experimental treatment conditions of the Main Study and attention to the Fed's February 2024 meeting (upper panel) and expected mortgage rate (lower panel). We measured the attention to the meeting and elicited expected mortgage rates in the Main Study. We use OLS estimations. Robust HC1 standard errors are reported. *p<0.1; **p<0.05; ***p<0.01

Table S7: Belief Updating and Willingness to Sell (Follow-up Study)

	(1)	(2)	(3)
Seller's Market Signal	0.003	0.001	0.01
	(0.04)	(0.05)	(0.20)
Belief updating (Follow-Up)	−0.01	−0.01	−0.01
	(0.01)	(0.01)	(0.01)
Expected Mortgage Rate (Follow-Up)		0.005	0.01
		(0.02)	(0.02)
Seller's Market Signal * Belief updating (Follow-Up)	0.03***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)
Seller's Market Signal*Expected Mortgage Rate (Follow-Up)			−0.002
			(0.03)
Constant	0.24***	0.21**	0.21
	(0.03)	(0.10)	(0.14)
N	416	416	416
Rsq	0.02	0.02	0.02

Note: This table presents the relationship between belief revisions and WTS in the Follow-up Study. We restrict our analyses to On-Market homeowners. OLS regression coefficients and robust HC1 standard errors are reported. *p < 0.1; **p < 0.05; ***p < 0.01

Online Calculator To Facilitate Learning



Note: All intervals were empty when participants started exploring the calculator.

WTS measure

consider_sell

Do you consider selling the property you live in within the next 12 months?

- ○ Not at all (0% probability)
- ○ There is a tiny probability that I will consider selling
- ○ There is a very small probability that I will consider selling
- ○ There is a small probability that I will consider selling
- ○ There is a medium probability that I will consider selling
- ○ There is a high probability that I will consider selling
- ○ There is a very high probability that I will consider selling
- ○ I will definitely consider selling

Token Allocation

Please allocate 100 points among housing price change intervals. Here 1 point = 1% chance. Remember that you should allocate points reflecting your expectations of each interval's probability of happening.

The average house price in my zip code will go up by at least 4% from August 2023 to August 2024	0 %
The average house price in my zip code will go up by about 3% to 3.99% from August 2023 to August 2024	0 %
The average house price in my zip code will go up by about 2% to 2.99% from August 2023 to August 2024	0 %
The average house price in my zip code will go up by about 1% to 1.99% from August 2023 to August 2024	0 %
The average house price in my zip code will go up by about 0.01% to 0.99% from August 2023 to August 2024	0 %
The average house price in my zip code won't change from August 2023 to August 2024	0 %
The average house price in my zip code will go down by about 0.01% to 0.99% from August 2023 to August 2024	0 %
The average house price in my zip code will go down by about 1% to 1.99% from August 2023 to August 2024	0 %
The average house price in my zip code will go down by about 2% to 2.99% from August 2023 to August 2024	0 %
The average house price in my zip code will go down by about 3% to 3.99% from August 2023 to August 2024	0 %
The average house price in my zip code will go down by at least 4% from August 2023 to August 2024	0 %
Total	0 %